CASEWORKER FACTORS THAT INFLUENCE REMOVAL DECISIONS IN CHILD WELFARE INVESTIGATIONS

by

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ABSTRACT

Child welfare agencies across the United States investigate millions of allegations of child maltreatment, including abuse and neglect, every year. Approximately 15% of the youth involved in these investigations are removed from their homes. Removals are tremendously impactful and change the trajectory of the lives of children and their families for better or worse.

Despite the extreme importance of the decision to remove children from their homes, these decisions are not always made systematically. Decisions are known to vary between workers—beyond variance attributable to the presence of child and family risk factors. There is limited information on what influences this variance. This study explored whether caseworker factors influence removal decisions using real-world data. Caseworker factors explored included demographics, experience, attitudes toward child safety and family preservation, and childhood history of adverse events. The results from this study suggested caseworkers with more experience, male caseworkers, and caseworkers with more ACEs are less likely to remove children from their homes. Each of these are potential areas that could be targeted by policy or practice interventions to reduce inconsistencies in removal decisions. The findings from this study contribute to the growing body of empirical research on CPS decision making, furthering knowledge that can inform theory and child welfare practice.

To my girls, Lilah and Siena.
May you continue to be strong, independent, and fearless.

TABLE OF CONTENTS

LIST OF TABLES

Tables

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CHAPTER 1

INTRODUCTION

In 2014 approximately 3,119,309 children in the United States (US) were referred to child welfare agencies for suspected child maltreatment (Children's Bureau, 2016). Of these referrals, 1,892,231 (60%) resulted in a Child Protective Services (CPS) investigation or an alternative child welfare response. In Utah, 213,448 children were referred to the Division of Child and Family Services (DCFS) for suspected maltreatment (Children's Bureau, 2016). These referrals resulted in a total of 20,294 CPS investigations (Division of Child and Family Services [DCFS], 2014). Approximately 60% of the maltreatment allegations were supported and 15% of those youth were placed into foster care (DCFS, 2014).

There are multiple decisions made when children are brought to the attention of child welfare agencies. After suspected maltreatment is reported, the first decision is whether to begin an investigation. Once the investigation is completed, the Child Protective Services (CPS) investigator must decide whether there is sufficient evidence to support the allegation. Next, the CPS caseworker determines the child's risk of experiencing future maltreatment. Finally, the caseworker must determine whether the child can remain in the home safely or should be removed and placed in out-of-home care. Each decision has the potential to profoundly impact the child and family involved for better or worse (Dettlaff et al., 2015).

The level of risk of future maltreatment is difficult to determine; studies have found considerable disagreement between caseworkers, including when using actuarial or structured risk assessment instruments (Bartelink, van Yperen, & Ingrid, 2015). Even when using risk tools reliably, maltreatment cannot always be predicted and the side on which to err, child safety or family preservation, is not clear as both can have disastrous impacts on the child and family (Baumann, Fluke, Dalgleish, & Kern, 2014). Children left in a home environment can suffer from further abuse or neglect, an outcome child welfare agencies wish to avoid. However, children removed from their homes and placed into foster care also experience poor long-term outcomes (Pecora et al., 2005).

Assessment of risk is further complicated because child welfare agencies vacillate between a focus on child safety and family preservation (Fluke, Corwin, Hollinshead, & Maher, 2016). In the U.S., the focus on child safety or family preservation can shift because of national perceptions of best practice. The shift in emphasis of different outcomes, either a lack of further child maltreatment or maintaining the family unit, can also influence focus (Fluke et al., 2016). Individual caseworkers or local agencies can fluctuate in their emphasis on child safety or family preservation as a result of serious outcomes, such as a child fatality (Mansell, 2006).

Despite the extreme importance of removal decisions, these decisions are known to vary between caseworkers, beyond variance expected due to child and family risk factors (Dettlaff et al., 2015; Fluke et al., 2014; Gold et al., 2001; Rossi et al., 1999). Moreover, there is little clarity on what factors best explain this variance (Graham et al., 2015). This type of variance is undesired because decisions are not made systematically;

children and family with similar circumstances may be subjected to different decisions simply by being assigned to different caseworkers.

Statement of the Problem and Research Questions

Ideally, CPS caseworkers would receive a referral, investigate an allegation of maltreatment, assess risk of future child maltreatment, and make a decision about the case in a rational manner, based solely on the facts of the case. Such decision making would help ensure consistent decisions are made for each child and family that come into contact with child welfare agencies. However, empirical data on general decision making suggests people are not consistent or wholly rational in their decisions and that there are other factors that influence decisions (Kahneman & Tversky, 1979). In child welfare, there is significant variance in decisions that is not related to risk factors in the case that should predict CPS decisions (Dettlaff et al., 2015; Fluke et al., 2014; Rossi et al., 1999). Furthermore, this unexplained variance has not been reduced to satisfactory levels given the introduction of structured and actuarial risk assessment tools (Bartelink et al., 2015).

In this study, I investigated if caseworker factors influence caseworkers' decisions to remove children from their homes at the point of CPS maltreatment investigations. Caseworker factors included characteristics such as their gender, minority status, and years of experience. I also explored whether caseworkers' attitudes toward child safety and family preservation and the presence of childhood histories of adverse experiences predicted removal decisions.

To explore variance due to caseworker factors, I explored if other pertinent factors predict removal to control for that variance. Specifically, I explored whether the region in which the case was investigated and the case characteristics predicted removal decisions. Case characteristics included the child's age, gender, race and ethnicity, as well as the number of previous times the child was involved in a supported CPS investigation. The term "supported" refers to the outcome of an investigation where an allegation of maltreatment was found to have merit by the CPS caseworker.

I utilized secondary data from Utah's statewide child welfare database and surveys that were administered to CPS caseworkers to answer these questions. These data were collected during an evaluation of the effectiveness of a Utah's IV-E Waiver Demonstration Project, a statewide intervention program conducted by DCFS. Use of these secondary data will be an effective and efficient method for answering these pertinent research questions.

CHAPTER 2

LITERATURE REVIEW AND RESEARCH QUESTIONS

This chapter has three sections: a review of general decision-making theories, a review of a child welfare decision-making framework, and a review of empirical studies. In the first section, I review general decision-making theories, theories that are not situated within any particular context. This includes a review of expected utility theory, prospect theory, heuristics and biases, and the motivation and opportunity as determinates of the attitude-behavior relation model. In the second section, I review the Decision-Making Ecology, which is a framework for understanding decisions within the context of child welfare. In the third section, I review empirical studies that have explored factors that influence child welfare decisions at the point of CPS investigation.

Theories of Decision Making

The following section is a review of general theories of decision making. A review of these theories is important because research within the child welfare context is relatively new and knowledge is limited. Thus, it is imperative to understand the field of general decision making to fill in gaps in knowledge and to assist in informing the direction of future child welfare decision-making research. In addition to contemporary perspectives on general decision making, early decision-making theories will be reviewed to provide background and context.

Rational Decision Making

Early decision-making theories were heavily influenced by 18th-century philosophers in the Age of Reasoning, a time in which rational thought was dominant. These theories propose that when faced with decisions, individuals seek alternatives and choose the option that will be of most value to them. Social exchange theory, for example, suggests that individuals consider the costs and benefits of all options before action is taken (Emerson, 1976). In his writing on how social exchange theory can explain behavior, Homans (1958) indicated human behavior can be best predicted by “how much value his behavior is getting him now,” rather than an individual’s values or reinforced behaviors (p. 599).

Expected utility theory, a rational-choice theory, is one of the foremost influential theories impacting contemporary decision-making theories (Wakker, 2010). Stemming from the writings of mathematician Daniel Bernoulli in the 18th century and the utilitarian philosopher Jeremy Bentham in the 18th and 19th centuries, expected utility theory attempts to explain how decisions under risk or uncertainty are made (Kahneman, Wakker, & Sarin, 1997; Moscati, 2016). In decision making, the term “risk” is used when probabilities of outcomes are known. The term “uncertainty,” sometimes referred to as ambiguity, is used when probabilities of outcomes are unknown (Wakker, 2010). The primary principle of expected utility theory is that an individual would consider the probabilities of the outcomes of a choice and rationally choose the option “with the highest expected utility” (Moscati, 2016, p. 219). The expected utility of an outcome can be calculated by multiplying the utility, such as the dollar amount of an outcome, by the probability of that outcome. Utility is not limited to monetary outcomes and can include emotional states such as happiness or satisfaction (Friedman & Savage, 1952) .

In the mid-20th century, the work of economists and mathematicians helped further develop expected utility theory (Moscati, 2016). This included the work of John von Neumann and Oskar Morgenstern who developed axioms to explain and predict the strategies and decisions of game players, known as game theory (Von Neumann & Morgenstern, 1944, 1947, 2007). Mishra (2014) provided the following summary of those axioms:

1. Completeness: Decision makers can always rank preferences between outcomes.
2. Transitivity: Preferred rank ordering of options is always consistent.
3. Continuity: There is some possibility that decision makers are indifferent between best and worst outcomes
4. Monotonicity: For outcomes with equal expected values, higher probability outcomes are preferred.
5. Independence: If paired choices are mixed with another set of paired choices, preferences remain independent. (p. 282)

Game theory assumes individuals, such as players in a game, will act rationally and use strategy to achieve an outcome with the greatest expected utility. The expected utility hypothesis and axioms of game theory have been applied in many fields to predict and explain decisions in various fields of study, including games of strategy (Dixit, Skeath, & Reiley, 2014), economics (Friedman, 1990), biology (Weibull, 1995), political science (Morrow, 1994), and public policy (Scharpf, 1997).

Bounded Rationality

Herbert Simon, however, stated that the "optimizing strategy" inherent in rational decision-making theories is rarely possible (Simon, 1990, p. 6). Instead, he indicated, "because of the limits on their computing speeds and power, intelligent systems must use approximate methods to handle most tasks. Their rationality is bounded" (Simon, 1990, p. 6). In other words, an individual's ability to make a rational decision is limited, or bounded, by his or her cognitive processing ability and the knowledge they have at the time of the decision. Simon (1982) used the term *satisficing* to describe the process of judgment and decision making, meaning that because an optimal choice cannot be made, an individual must instead settle for the most satisfactory option.

Nevertheless, Simon (1990) noted an individual's level of competence must also be considered. He asserted that an individual with expertise in a subject area "can reach solutions that are unattainable by the novice" (Simon, 1990, p. 7). This is because previously acquired knowledge and skills are not stored in the working memory areas of the brain and therefore do not impact the ability to process information in the moment. Instead, researchers find that experts use methods such as chunking and pattern recognition to quickly analyze information needed to make decisions (Chase & Simon, 1988; Gobet et al., 2001; Miller, 1956).

Prospect Theory

Rational choice theories have dominated research in judgment and decision-making; however, many researchers found fault with the idea of rational decision-making and expected utility theory. As discussed above, Mishra (2014) highlighted problems in the definition of utility when he noted the utility of a decision can take various forms, making it difficult to define what outcome has the highest expected value. Accordingly, Mishra indicated that it is possible to argue any choice maximizes some utility. This means that every option has some value that would not be achieved given a different selection. Additionally, researchers such as Daniel Kahneman and Amos Tversky find this theory fails to accurately predict decision-making behavior.

In a study that typified their research agenda, Kahneman and Tversky (1979) presented subjects with hypothetical gambles and found individuals often violated the axioms of the theory when making judgments and decisions. For example, the participants were given a choice between an 80% chance of winning $4,000 (an expected utility of $3,200) or a guarantee of $3,000 (an expected utility of $3,000). According to expected utility theory individuals should choose the first option that has the greatest expected monetary utility. However, approximately 80% of the participants chose the latter, violating the primary tenet of expected utility theory (Kahneman & Tversky, 1979).

Kahneman and Tversky (1979) also noted an interesting phenomenon with some of the tasks. In contrast to the findings described above, the individuals' preferences were reversed when the problems involved losses. That is, given the choice between an 80% chance of losing $4,000 (an expected utility of -$3200) or guarantee of losing $3000 (an expected utility of -$3000), 92% of the participants chose the former option. Again, this preference is inconsistent with expected utility theory and the supposition that rational thought governs choices (Kahneman & Tversky, 1979).

As a result of their research findings, Kahneman and Tversky developed prospect theory (1979), which they later developed into cumulative prospect theory (Tversky & Kahneman, 1992) as an alternative to expected utility theory. Stepping away from the assumption that individuals are rational in their judgments and decision making, prospect theory contends decisions are made in two phases: editing and evaluation (Kahneman &

Tversky, 1979).

During the editing phase the questions are simplified and coded as gains or losses. The coding process is influenced by an individual's position, or reference point, at the time of a judgment or decision (Kahneman & Tversky, 1979). For example, Kahneman and Tversky suggested a business person would code outcomes differently under the condition of a recent revenue loss than he or she would otherwise. During the evaluation phase, the outcomes are deliberated and an option is chosen. Further, individuals unconsciously weight the probabilities of outcomes; outcomes with small probabilities are overestimated and outcomes with moderate and high probabilities are underestimated.

Framing Effects

Tversky and Kahneman (1992) emphasized that an individual's subjective judgments are unlikely to "conform to the rules of probability theory" due, in part, to the way the choice is presented (p. 317). For example, Tversky and Kahneman (1981) presented subjects with the Disease Problem in which the respondents were provided the same problem with different frames of reference. In problem one, the participants were asked to choose between Program A where 200 lives would be saved or Program B which had a one-third probability of saving 600 lives. In the second problem, respondents were asked to choose between Program C where 400 individuals would die or program D which had a two-thirds probability 600 people would die. Individuals should prefer A and C or B and D, as these choices are equivalent. Nevertheless, Tversky and Kahneman found individuals favored A and D, rather than the inversely framed corresponding choices. Indeed, researchers have found framing effects, or frames of reference, are influential when making judgments in many fields (Covey, 2014; De Haan & Van Veldhuizen, 2015; Desser, Olsen, & Grepperud, 2013; Frisch, 1993; Gallagher & Updegraff, 2012; McNeil, Pauker, Sox Jr, & Tversky, 1982; Mishra, Gregson, & Lalumiere, 2012; Sieck & Yates, 1997; Smith & Levin, 1996; Stanovich & West, 1998; Tversky & Kahneman, 1981).

Though judgments and choices can be readily influenced by frames of reference, framing effects are moderated by other factors related to the task. For example, researchers have found framing effects were reduced when research subjects were asked to provide rationales for their judgments and decisions (Almashat, Ayotte, Edelstein, & Margrett, 2008; S. Kim, Goldstein, Hasher, & Zacks, 2005; P. M. Miller & Fagley, 1991; Sieck & Yates, 1997; Takemura, 1992). Moreover, researchers have found framing effects were further reduced when individuals were asked to provide a rationale for a choice prior to making their selection (Sieck & Yates, 1997) or were asked to explain their choice to others (A. Simon, Fagley, & Halleran, 2004).

In addition to task-related factors, researchers have found framing effects are moderated by factors related to the decision maker. Using the Disease Problem described above, Stanovich and West (1998) found individuals with higher intellectual capacity were less susceptible to framing effects. Similarly, studies have found reduced framing effects in individuals who have a higher need for cognition, that is, they are prone to analytic thinking or reflection (Covey, 2014; LeBoeuf & Shafir, 2003; Smith & Levin, 1996).

Dual-Process Models of Judgment

Kahneman and colleagues conducted numerous studies to understand the mechanisms involved in judgment and decision making (see Kahneman, 2003, for an overview). Over time, they observed that when confronted with a judgment problem or decision, research subjects frequently came up with a rapid, or intuitive, response (Kahneman, 2003). Those intuitive responses, Kahneman and Frederick (2002) suggested, can be highly error prone and non sequitur. This faulty intuition is not restricted to lay persons. Tversky and Kahneman (1971) discovered faulty logic when judgments were made without deliberate thought or calculation even when the respondents were experts in the subject area. The investigators presented questions about sample size to researchers who attended a conference for the Mathematical Psychology Group and American Psychological Association. They found that the researchers performed poorly on the tasks, despite having ample knowledge and practice experience.

Kahneman (2003) acknowledged that it is apparent that when individuals are more deliberate or thoughtful in their judgments, they are capable of reducing errors and inconsistencies (P. M. Miller & Fagley, 1991; Sieck & Yates, 1997; Takemura, 1992). This collective work led Kahneman and colleagues to understand judgment and decision making as two distinct cognitive processes. This conclusion brought their work within the field of dual-process theories. Dual-process theories of reasoning have been investigated and deliberated by many researchers and theorists (Chaiken, Liberman, & Eagly, 1989; Epstein, 1994; Evans, 1984; Evans & Over, 1996; Fazio, 1990; Hammond, 1996; Johnson-Laird, 1983; Levinson, 1995; Petty & Cacioppo, 1986; Reber, 1989; Shiffrin & Schneider, 1977; Sloman, 1996). To explicate the commonalities of the various models proposed, Stanovich and West (2000) used the term System 1 to refer to the intuitive response in decision making and the term System 2 to refer to the deliberate processes used in decision making.

Kahneman (2003) adopted the terms put forward by Stanovich and West (2000), describing the operations of System 1 as "typically fast, automatic, effortless, associative, implicit (not available to introspection), and often emotionally charged; they are also governed by habit and are therefore difficult to control or modify" (p. 698). The role of System 1 is to find mental shortcuts to help minimize cognitive efforts required for many tasks, judgments, and decisions. The cognitive processes involved in System 2 are "slower, serial, effortful, more likely to be consciously monitored and deliberately controlled; they are also relatively flexible and potentially rule governed" (Stanovich & West, 2000, p. 698). System 2 is responsible for higher order reasoning and is capable of meta cognitions (Evans & Stanovich, 2013; Stanovich & West, 2000). If triggered, the analytic and thoughtful System 2 can override the automatic processes in System 1 (Kahneman, 2003; Stanovich & West, 2000). Though the term judgment is used to refer to conclusions made by both systems, Kahneman (2003) is careful to differentiate *intuitions*, which are made quickly by System 1, and *reasoning*, made by means of deliberate analysis in System 2.

In efforts to understand the differential processes involved in judgment and decision making, investigators have attempted to discover what mechanisms activate each system. Some researchers have found that the characteristics of individuals can influence which system is activated. As discussed above, participants at different levels of cognitive ability and need for cognition display differences in response patterns

(Covey, 2014; LeBoeuf & Shafir, 2003; Smith & Levin, 1996; Stanovich & West, 1998). These differing response patterns reflect differential activation of the two systems between individuals. Researchers have also found that knowledge in a subject area will impact which of the cognitive processes are activated (Lecheler & de Vreese, 2012). The mood of the individual can impact judgment and decision making (Bless et al., 1996; Isen, Nygren, & Ashby, 1988; Lecheler, Schuck, & de Vreese, 2013), as can their mental preoccupation (Gilbert, 1989).

Task limitations and the type of problem an individual is undertaking can likewise impact which system is activated (Kahneman & Frederick, 2002; Stanovich & West, 2000). Kahneman and Frederick (2002) stated that unfamiliar tasks, abstract problems, and "deliberate application of rules" invoke System 2 responses (p. 2). Additionally, studies have demonstrated that the imposition of time limitations will result in limited use of analytic operations (Beach & Mitchell, 1978; Finucane, Alhakami, Slovic, & Johnson, 2000; Kerstholt, 1994) and can promote riskiness in decision making (Ben Zur & Breznitz, 1981).

Accessibility

Kahneman (2003) suggested that reliance on System 1 or System 2 is, in part, driven by accessibility. He defined accessibility as "the ease (or effort) with which particular mental contents come to mind" (Kahneman, 2003, p. 699). This means that when presented with a decision, the mind will begin with stored information that is readily accessible. If a response or solution is accessed quickly, or intuitively, the cognitive processes will stop there. In the event that relevant data are not easily accessed and there is sufficient time for processing, System 2 operations will begin the deliberate, analytical processing of information. Kahneman (2003) indicated that the accessibility of information can be influenced by factors such as salience, attention, training, association, and priming. These ideas will be discussed further in the Heuristic and Biases section below.

The role of the analytic processes of System 2 is to monitor, vet, or correct the automatic response of System 1. However, Kahneman and Frederick (2002) noted that the supervisory role of System 2 can be quite lax. Kahneman (2003) proposed the following model for the interacting operations of System 1 and System 2:

> 1. An intuitive judgment or intention is initiated and
>   (a) endorsed by System 2,
>   (b) adjusted (insufficiently) for other features that are recognized as relevant,
>   (c) corrected (sometimes overcorrected) for an explicitly recognized bias, or
>   (d) identified as violating a subjectively valid rule and blocked from overt expression.
> 2. No intuitive response comes to mind, and the judgment is computed by System 2 (p. 717).

Therefore, according to this model, the rapid processing operations of System 1 will quickly come to a conclusion when presented with a judgment task. System 2 may hastily approve the supposition—without intensive analytical cognitive processes. Kahneman and Frederick (2002) referred to this approval without modification as an intuitive response. If the conclusion is not approved System 2 will either adjust or substitute a new conclusion using cognitive operations that require deliberate attention and systematic analytical thought. Additionally, as discussed above, System 2 will be activated if a rationale for the System 1 conclusion is necessary. Finally, System 2 will assume control if no information is easily accessed by the intuitive process of System 1.

Heuristics and Biases

Attribute Substitution

If many of our judgments and decisions rely on the automated, and potentially biased, intuitions of System 1 then it is crucially important to understand how this system processes information. In their seminal article in this subject area Tversky and Kahneman (1974) concluded that people "rely on a limited number of heuristic principles which reduce the complex task of assessing probabilities and predicting values to simpler judgmental operations" (p. 1124). In other words, general heuristic rules are applied to reduce the level of cognitive effort required. Later, Kahneman and Frederick (2002) modified these suppositions and added that attribute substitution underlies all heuristic operations. That is, so long as the analytic and meta-cognitive processes of System 2 do not override when System 1 is presented with a difficult judgment, the mind will attempt to quickly obtain relevant data. If no such information is found, System 1 will rely on attribute substitution, a process by which the mind will attach the attributes onto similar attributes to find a suitable answer. Kahneman and Frederick (2002) proposed the following guiding principles for attribute substitution:

> Attribute substitution occurs when the target attribute is assessed by mapping the value of another attribute on the target scale. This process will control judgment when three conditions are satisfied: (1) the target attribute is relatively inaccessible; (2) a semantically and associatively related candidate attribute is highly accessible; and (3) the substitution of the heuristic attribute in the judgment is not rejected by the critical operations of System 2. (p. 5)

To illustrate attribute substitution, Kahneman and Frederick (2002) provided an example from a study conducted by Strack, Martin, and Schwarz (1988). In it, Strack and colleagues asked participants how happy they were with life in general and how many dates they had in the last month. The investigators found the correlation of the participants' responses rose significantly when asked the former question first. The investigators concluded the information required to respond to the specific question, how many dates, was more easily retrieved and quantified than the information required to assess the more abstract concept of happiness. The participants then used the more accessible information to substitute for gaps in information related to overall happiness. More recent studies have found evidence of attribution substitution in areas ranging from belief in global warming (Zaval, Keenan, Johnson, & Weber, 2014) to diagnoses made by internal medicine residents (Phang, Ravani, Schaefer, Wright, & Mclaughlin, 2015).

System 1 Heuristics

As discussed above, Tversky and Kahneman (1974) indicated that when individuals are presented with a choice or decision, they process the information according to some heuristic rule. Researchers have found individuals unknowingly rely on heuristics in a variety of decision-making settings, from problems in appraising the distance of an object to judging one's own mood (Kahneman & Frederick, 2002). Bias in judgment and decision making is then introduced because of these heuristic rules. That is, the errors due to the use of heuristics are systematic rather than random (Evans, 1984).

Tversky and Kahneman (1974) proposed that, though they are frequently applied, there are three primary heuristics used to process information. First, they introduced the *representativeness heuristic*, which is used when individuals are asked to make a probability judgment. According to this heuristic, if individuals are asked whether some event is a result of some other occurrence, they will assess whether the two are similar and draw their conclusion without considering the actual probability of the event. For example, Tversky and Kahneman (1974) presented participants with the following description of a male: he has a “meek and tidy soul, he has a need for order and structure, and a passion for detail” (p. 1124). They then presented the subjects with a list of occupations (farmer, librarian, etc.) and asked which the man was most likely to be. The participants frequently choose librarian which Tversky and Kahneman posited was as a result of the description which resembled that of a stereotypical librarian. The researchers pointed out, however, the man was more likely to be a farmer because there are far more male farmers than male librarians. Tversky and Kahneman concluded that when individuals are making judgments and decisions, they are insensitive to probabilities of outcomes.

The second heuristic introduced by Tversky and Kahneman (1974) is the *availability heuristic*. According to this heuristic, individuals will assess the frequency of an event by the ease in which examples of the event come to mind. Though the availability heuristic may often be accurate because frequent events are more accessible (easily recalled) than infrequent events, availability can be skewed by factors such as the emotional salience of an event rather than the actual frequency of the occurrences. The authors suggested the emotional impact of seeing a home on fire, for example, would bias an individual’s perception of the frequency of house fires.

Initially, Tversky and Kahneman (1974) named *anchoring* as a third primary heuristic. Anchoring, they indicated, is an observed phenomenon in which a response is influenced by an initial suggestion—that is, the response remains close to, or ‘anchored to,’ the suggestion. While anchoring has been found to influence behavior, Kahneman and Frederick (2002) later indicated it does not fit their definition of a heuristic because attribute substitution is not used in anchoring. Instead, they admitted that in their earlier writings they missed a crucial heuristic, the *affect heuristic*. The affect heuristic indicates that individuals are likely to unknowingly substitute a judgment question with information on how they feel about the object in question.

Choice Heuristics

Choice theories differ from Kahneman and Tversky's heuristics and biases approach in that they explore the conscious use of heuristics in System 2. Frederick (2002) defines deliberate choice heuristics as "conscious strategies that are intentionally designed to simplify choice" (p. 548). Unlike the heuristics discussed above, the individual applying the heuristic is aware of this and can explicitly modify the heuristic if desired. For example, Gigerenzer, Todd, and ABC Research Group (1999) proposed fast and frugal heuristics, which can be conscious or unconscious mental shortcuts for making complex decisions. They provide evidence that heuristics can help guide mental searches for information, stop searches, and make quick decisions. The researchers demonstrated that individuals can be as accurate in solving complex problems when heuristics are applied as when complex analysis is conducted. However, the former proved to be a more efficient method because real-world environments do not always allow for necessary deliberation (Gigerenzer & Goldstein, 1996).

The Development of Skilled Intuition

Although System 1 is fallible and can lead to bias, this is not always the case. Stanovich and West (2000) highlighted that, though the use of heuristics and resulting biases appear to be universal, the types of errors are not universal because some individuals “have the requisite computational power (or low enough threshold) to override the response of System 1” (p. 660). Additionally, echoing Simon’s (1990) ideas on the rapid processing abilities of experts (discussed in the Bounded Rationality section above), Kahneman and Frederick (2002) posited, “complex cognitive operations eventually migrate from System 2 to System 1 as proficiency and skill are acquired” (p. 3).

Kahneman admitted his study of heuristics and biases focused on faulty intuition; however, he indicated his model is not incompatible with studies of expert intuition (Kahneman & Klein, 2009). He stated heuristics can be shaped by knowledge gain and the acquisition of skills, which will influence the accessibility of that information. The question then becomes, under what conditions do expert intuitions develop what Kahneman referred to as “true intuitive skill,” as opposed to “overconfident and biased impressions” (Kahneman & Klein, 2009, p. 515). Expertise can be defined as “outstanding performance or ability” (Ericsson & Smith, 1991, p. 3) that an individual can reproduce (Ericsson, Roring, & Nandagopal, 2013).

Investigation into this subject area began with observations by Chase and Simon (1988), who determined master chess players have the ability to rapidly perceive as many as 100,000 patterns and choose an optimal move. This led to the definition of skilled intuition as the recognition of patterns and cues. H. A. Simon (1992) stated, “The situation had provided a cue: This cue has given the expert access to information stored in the memory, and the information provides the answer. Intuition is nothing more and nothing less than recognition” (p. 155).

The definition of intuition as recognition of cues and patterns was adopted by Kahneman to explain skilled intuition within the heuristics and biases approach (in Kahneman & Klein, 2009). Kahneman and Klein (2009) added that for recognition to take place, two conditions must be satisfied: "First, the environment must provide adequately valid cues to the nature of the situation. Second, people must have an opportunity to learn the relevant cues" (p. 520). Valid cues are cues that accurately predict an event and are observable. Kahneman and Klein (2009) provided an example of nurses in infant units who can detect the subtle signs of infection or firefighters who can look at a structure and discern signs of impending collapse.

In addition to the requirements of recognition, Kahneman and Klein (2009) proposed there are two conditions necessary for the development of skills that lead to expertise: "an environment of sufficiently high validity and adequate opportunity to practice the skill" (p. 520). High-valid environments are environments that are predictable. Within this predictable environment, an individual can begin to develop expertise by recognizing cues and patterns. However, it is training and skill practice, not experience, that influences expertise (Camerer & Johnson, 1991). Ericsson (2006) highlighted that expertise does not develop until there has been prolonged skill practice. Skills should be learned sequentially, with graduated difficulty, and include accurate and immediate feedback from a knowledgeable instructor (Ericsson & Smith, 1991; Kahneman & Klein, 2009; Shanteau, 1992)

Even well-training individuals, however, predict events less accurately than statistical models (Camerer & Johnson, 1991). This is partially due to individuals relying on extraneous cues and weighting cues inconsistently. Kahneman and Klein (2009), for example, highlighted that there are some conditions in which feedback may be misleading and can lead to overconfidence and bias. For example, in professions such as counseling, psychotherapists may receive immediate feedback during a session; however, they are unlikely to receive feedback on the long-term outcome of that client (Tracey, Wampold, Lichtenberg, & Goodyear, 2014). Consequently, therapeutic interventions are reinforced by immediate feedback and short-term outcomes and may be unhelpful in achieving ultimate goals.

Additionally, there are circumstances for which there are no valid cues and outcomes are not predictable. This includes situations such as predicting the performance of the stock market, predicting long-term political events, or predicting the winning numbers in a lottery (Kahneman & Klein, 2009). Kahneman and Klein (2009) indicated that under these conditions, where there are no valid cues and events are not sufficiently predictable, it is not possible to develop expertise.

Attitudes and Decision Making

The impact of attitudes is notably missing in the above theories. In a review of literature on decision making and attitudes, Sanbonmatsu, Prince, Vanous, and Posavac (2005) found the impact of attitudes on decisions was frequently overlooked. The researchers suggested attitudes have not been disregarded due to the unimportance of the construct in decision making, but that the influence of attitudes is ignored because of the narrow focus of decision-making research and a general lack of fluency with literature on attitudes. Sanbonmatsu et al. (2005) explained that attitudes influence decisions by impacting assessment of the situation, or decision to be made, information related to the choice, goals of the choice, and options available.

Sanbonmatsu et al. (2005) defined attitudes as “the feelings and evaluations associated with a representation of an object in memory” (p. 102). Objects can take a variety of forms including “persons, objects, events, situations, routines, instructions, goals, positions, ideas, behavior, and issues” (p. 102). Another broadly accepted definition was put forth by Eagly and Chaiken (1993), who described attitudes as “a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor” (p. 1). While research on decision making has overlooked the influence of attitudes, researchers within the field of social psychology have explored the influence of attitudes on choices and behaviors. The following is a review of one model of the impact of attitudes on behavior.

MODE Model

One attitude-based model relevant to the field of decision making is a model created by Fazio (1990), the motivation and opportunity as determinates of the attitude-behavior relation (MODE) model. The MODE model is a dual-process model for understanding the impact of attitudes on perceptions and behaviors. It integrates two attitude-behavior theories: spontaneous processing model (Fazio, 1986) and the theory of reasoned action (Ajzen & Fishbein, 1980).

The MODE model suggests that when there is low motivation, such as a low-cost decision, or there is a lack of opportunity, such as lack of time, an individual will use the spontaneous processing model. The spontaneous processing model suggests that, when in a situation, global attitudes can be automatically activated and influence perceptions without deliberate consideration of the attitude. In other words, the influence of attitudes on behaviors is automated and unconscious. To use the language used above, the attitude will influence the decision or behavior in System 1.

Alternatively, when motivation is high and there is ample opportunity to deliberate, the MODE model hypothesizes that the cognitive process described in the theory of reasoned behavior will override the automated processes described above. Both motivation and opportunity must be present to activate reasoned behavior. Additionally, if a global attitude is not readily accessible an individual may be forced into more deliberate processes (Sanbonmatsu et al., 2005), or System 2. According to the theory of reasoned action, behavioral intentions are shaped by the individual's attitude toward the behavior and the subjective norm, or what the individual believes others think he or she should do (Ajzen & Fishbein, 1980). It is important to note that within this model attitudes are specific to situations, rather than global attitudes.

Gaps in Decision-Making Theories

While tremendously informative in understanding the processes used in general decision making, many of the aforementioned theories have not consistently explored whether general decision-making principles apply across different settings and contexts. While there is disagreement on whether judgment and decision making are stable across settings, referred to as domain-general, or contextually driven, referred to as domain-specific, many of these theories have largely ignored the issue and appear to assume decisions are context free (Mishra, 2014). As such, it is unclear if these general decision-making theories can explain behaviors in other settings. In his review of decision-making theories, Mishra (2014) concluded, “The theoretical perspectives and evidence reviewed above suggest that risk-taking is by default domain-specific but can manifest as being domain-general” (p. 296). Therefore, it is imperative to determine the applicability of these general decision-making theories within the child welfare setting.

The Decision-Making Ecology

Researchers created the Decision-Making Ecology (DME), depicted in Figure 2.1, to integrate general theories of decision making and to organize decision-making research within the child welfare context (Baumann, Dalgleish, Fluke, & Kern, 2011; Baumann et al., 2014; Fluke et al., 2014). The DME framework was preceded by two earlier models for understanding child welfare work. A model by Stein and Rzepnicki (1983) helped frame the broader goals of child welfare systems. Stein and Rzepnicki highlighted the importance of decision making and sources of information for these decisions within the child welfare context. More recently, Munro (2005) created a framework for improving child protection in which she emphasized the need for a systemic approach to understanding errors made in child protection. She stated decision-making manuals and tools alone are unhelpful in reducing error. Instead, the reasons for the errors must be understood, including “why the faulty action had looked like the sensible thing to do at the time or why it might have been difficult for humans to perform well” (Munro, 2005, p. 377).

The authors of the DME framework echoed Munro’s sentiment and suggested that understanding child welfare decisions cannot happen without understanding the systemic context of the decisions and, thus, it is imperative to better understand factors that influence decision making (Baumann et al., 2011). They identified many factors that can influence decision making and organized those factors into four sources: organizational factors, external factors, case factors, and decision-maker (caseworker) factors (see Figure 2.1; Baumann et al., 2011).

Case factors that may influence removal decisions include the child and family demographics, risk score, and the nature of the incident that brought the child and family to the attention of the child welfare system. Organizational influences include factors such as organizational culture and climate as well as agency policies and practices. External factors are influences outside of the child welfare organization such as local culture, legal systems, and available community services. Finally, decision maker factors are influences related to the individual making the decision such as demographic characteristics, work experience, attitudes, and belief system. Variance from these four sources (represented by the ovals in Figure 2.1) will influence the decision (represented by the diamond), which will then impact the outcome (represented by the rectangle). Finally, the outcome of the decision will influence future decisions (represented by the large arrows pointing from the outcome back to the factor influences).

The DME framework attempts to understand decision making throughout the child welfare system, referred to as the decision-making continuum (Baumann et al., 2011, 2014; Fluke et al., 2014). Decisions along the continuum include decisions to open an investigation, initiate services, remove children from their homes, and reunify children with their families. Implicit in this framework is that decision thresholds vary and different outcomes are emphasized at each point of contact. Accordingly, decisions must be understood at each decision point and findings related to one decision point may not generalize to others (López, Fluke, Benbenishty, & Knorth, 2015).

General Assessment and Decision-Making Model

The General Assessment and Decision-Making Model (GADM; Baumann et al., 2014), depicted in Figure 2.2, is situated within the DME framework as a structure for understanding the psychological processes involved in decision making. There are two distinct actions within the GADM: a *judgment* and a *decision*. A judgment is the conclusion drawn regarding a case (represented by the left oval in Figure 2.2). Determining a child abuse allegation to have merit or assessing a situation to be unsafe are judgements. The decision is the action taken by the child welfare worker (represented by the right oval in Figure 2.2). After the investigation, caseworkers will make decisions whether to begin services with a family and whether to remove a child from a home, given their judgments of the situation.

The GADM is influenced by the concepts of hits and misses in signal detection theory (Dalgleish, 1988; Swets, Tanner, & Birdsall, 1961). In CPS decision making, hits, for example, are when children are rightfully removed from their home, that is, where leaving them in their home would have resulted in the children experiencing further serious maltreatment. Misses include false positives, where children are removed from their homes when they would not have suffered further serious abuse or neglect, and false negatives, where children are left in their homes and experience further maltreatment. It is impossible for child welfare caseworkers to avoid misses, but the side on which to err is not always clear, as both can have tragic impacts on the child and family (Baumann et al., 2014). A child who is removed and placed in out-of-home care when the home environment could have sufficed can experience just as poor long-term outcomes as a child who is not removed from a home and experiences further maltreatment.

The authors of the GADM model postulate there are decision thresholds that influence how judgments become decisions, an idea influenced by the concept of thresholds in signal detection theory (Dalgleish, 1988; Swets et al., 1961). Decision thresholds are defined as “the point at which the assessment of the case information (e.g., amount and weight of evidence) is intense enough for one to decide to take action” (Baumann et al., 2011, p. 7). Judgment and decision thresholds vary between caseworkers. For example, two workers may diverge on their judgment of a situation and disagree on the safety or risk assessment score for a child. Conversely, workers may judge the situation similarly; however, one worker may make the decision to intervene while the other would not. Decision thresholds can also be influenced by case, organizational, external, and decision-maker factors.

Gaps in Child Welfare Decision-Making Theory

Investigation into factors that influence decisions made within child welfare agencies is a relatively new field of study, and knowledge is limited. As such, much of the research is exploratory and child welfare decision researchers are largely unable to make specific predictions or provide explanations for how and which factors influence child welfare decisions. Additionally, researchers in this field have not reached consensus on which factors should be prioritized and there is a lack of agreement upon operationalization of pertinent variables. These problems can lead to inconsistent research designs and conflicting results. For example, as will be seen below, researchers have investigated how caseworker characteristics and attitudes regarding child safety and family preservation impact decisions. Some studies have found significant findings while others have not. These contradictory findings highlight a need for further investigation of the factors that influence decisions and a need for agreement on the operationalization of key variables in order to inform child welfare decision theories.

Empirical Research on Child Protective Service Decision Making

In this section, I review empirical research on decision making in CPS investigations. I chose to use the DME framework to organize this section, as it provides an effective structure for understanding the factors that influence decision making within child welfare settings. Studies were reviewed that investigated which case factors, organizational factors, external factors, and caseworker factors influence judgment (risk assessment) and decision making (removal decisions). Due to the variability of the factors that influence decisions at various points in child welfare services (Baumann et al., 2011, 2014; Fluke et al., 2014; López et al., 2015), only studies that focused on decisions made at the point of CPS investigation are included.

Case Factors

Case factors are significantly related to placement outcomes in many CPS decision-making studies and have frequently been found to be the largest predictors of variance in worker decisions (Font & Maguire-Jack, 2015; Graham et al., 2015). Case factors include factors related to the child, family, or maltreatment incident, such as the child and family demographics, presence of risk factors, type of maltreatment, and families' current circumstances. The following is an examination of empirical findings related to case factors.

Safety and Risk

A child's level of risk for re-abuse and neglect is a significant predictor of the decision to remove a child from his or her home (Graham et al., 2015; Rivaux et al., 2008). Graham et al. (2015), for example, found caseworkers' average risk assessment score predicted their removal rates. This was in the direction expected—greater average assessed risk was associated with increased average removal rates. It is worth noting, however, there are multiple problems with using risk assessment as a predictor. First, risk is determined using several different methods and tools in child welfare agencies, making it difficult to compare across studies. Additionally, actuarial risk assessments and structured decision-making tools used in child welfare have notoriously low interrater reliability and few have undergone criterion-validity studies (Bartelink et al., 2015). Finally, risk assessment tools are subjective and there is evidence caseworkers may adjust risk assessments to match removal decisions they have made (Graham et al., 2015). Thus, the same factors that influence decision making may also influence judgment of risk; this is discussed further in the limitations section below.

Child and Family Demographics

Researchers have found that children's race and ethnicity is predictive of scores on risk assessments and in removal decisions (Baumann et al., 2010; Dettlaff & Rycraft, 2008; Fallon et al., 2013; Graham et al., 2015; Rivaux et al., 2008; Wulczyn & Lery, 2007). Many of these studies found disproportionality in removal rates, with higher rates of removal for minority youth. There is also some evidence that decision thresholds for removal differ by racial and ethnic groups. Rivaux et al. (2008) found Caucasian youth with high risk scores were less likely to be removed than African American youth with high risk scores.

Nevertheless, there are also findings suggesting the opposite effect. Dettlaff et al. (2011) found higher removal rates for African American youth disappeared after controlling for income. Additionally, Fluke, Yuan, Hedderson, and Curtis (2003) found that while African American children are overrepresented in removals, they appear to suffer more instances of maltreatment. Findings such as these led Bartholet (2009) to conclude the overrepresentation of African American youth is not exclusively as a result of bias. Instead, she stated, minority youth appear to be disproportionately impacted by adverse circumstances that contribute to maltreatment, such as extreme poverty and parental substance abuse.

Current Maltreatment and Family History

Factors related to the specific child abuse or neglect incident that brought the family to the attention of CPS (e.g., the type of abuse or if there were parental perpetrators) and the family history of child welfare involvement have been found to be predictive of both risk assessment scores and removal decisions. For example, using vignettes, Stokes and Taylor (2014) found workers rated neglect as less risky than physical or sexual abuse. Rossi et al. (1999), also using vignettes, found that a child had an increased likelihood of removal if there was a failure of a caretaker to protect the child or if there were ongoing threats against the child. The family's case history was also found to be a significant predictor of removal, where children with a higher number of previously supported reports had an increased likelihood of removal. In this study the type of abuse, physical or sexual, was not influential on the removal decision.

Current Circumstances

The situation of the family at the time of the investigation is also predictive of removal decisions. Rossi et al. (1999) found a caseworker was more likely to recommend removal if the family was homeless or if the worker judged the current environment of the family to be dangerous. Cases where families had some source of income and demonstrated a desire to change were less likely to result in removal decisions. Other studies have also found poverty or low family income to be associated with the decision to remove children from their home (Enosh & Bayer-Topilsky, 2015; Graham et al., 2015; Rivaux et al., 2008). However, in one study in which the researchers analyzed child welfare administrative data, this disparity disappeared in communities where overall poverty rates were high (Wulczyn, Gibbons, Snowden, & Lery, 2013).

Organizational Factors

In addition to case factors, factors related to the organization, that is the child welfare agency, can influence the decision-making process. This can include factors such as the demographics of the child welfare service users, culture of an office, or agency policies. The influence can take place on a micro level, such as a team or office, or a macro level, such as county, state, region, or country. The following is an examination of empirical findings related to organizational factors.

Regional Differences

Rossi et al. (1999) administered a vignette to respondents in three states (Michigan, New York, and Texas) and found differences in the rates of recommended removal between the states. Participants from Texas were most likely to recommend removal, whereas those from New York were least likely to recommend removal. Similarly, Benbenishty et al. (2015) measured child welfare workers' attitudes toward removal in four countries: Israel, Northern Ireland, Spain, and the Netherlands. These survey responses were matched to vignettes completed by the workers. The researchers found significant differences between the countries on attitudes toward child safety, family preservation, and removal recommendations.

Service User Population

The client population involved in services and the local child welfare organizational structure have been found to impact removal decisions. Using child welfare agency data in Canada, Fluke, Chabot, Fallon, MacLaurin, and Blackstock (2010) and Fallon et al. (2015) found that higher proportions of investigations involving aboriginal children resulted in more out-of-home placements for all children. Later investigations with these data found this effect was mediated by the degree of centralization of the child welfare agencies (Chabot et al., 2013). Graham et al. (2015), however, found contrasting results. Using administrative data from Texas, the researchers found having a higher proportion of minorities on a worker's caseload led to lower overall removal rates.

External Factors

The DME framework postulated external factors influence decision making. External factors are influences from outside of child welfare organizations such as local culture, legal systems, and available community services. Despite their suggested influence, external factors have received little attention in studies. Some researchers have hypothesized that local service array influences placement decisions due to disproportional removal rates in areas with scarce community services (Dettlaff & Rycraft, 2008; Fluke et al., 2010; Font & Maguire-Jack, 2015).

It is also plausible legal partners influence removal decisions. To explore their role, Britner and Mossler (2002) looked at differences between social service workers and legal partners in investigative and removal decisions. They asked judges, guardians ad litem (GAL), mental health workers, and child welfare workers to rate the importance of different types of case information in making case decisions. The researchers found social workers and mental health workers were more interested in severity of abuse and previous amenability to treatment than judges and GALs. The legal partners considered the likelihood of repeat abuse, and the child's ability to describe the abuse, as most important. While removal decisions were not included in this study, the findings suggest there are differences in the type of information legal partners and child welfare workers attend to, which would likely impact removal recommendations.

Decision-Maker Factors

Finally, factors related to the decision maker, specifically the CPS caseworker, are important to consider. These factors include the caseworkers' demographics, years of experience, worker related experiences, and attitudes and beliefs. This section is an examination of empirical findings of caseworker factors.

Worker Demographics and Experience

Graham et al. (2015) found no direct relationship between the gender and years of experience with DCFS of the caseworker and removal decisions. Similarly, Font and Maguire-Jack (2015) found the amount of work experience and education of workers had no significant impact on removal decisions. However, other researchers have found contrasting outcomes. When surveying social service workers in Croatia and Sweden, Brunnberg and Pećnik (2007) found workers with more experience were less likely to recommend removal. Davidson-Arad, Englechin-Segal, Wozner, and Gabriel (2003) came to the same conclusion when they surveyed workers in Israel.

Role Differences

Rossi et al. (1999) used vignettes to assess differences in decision making between experts and workers. Experts were identified as individuals who had "some high standing in the child welfare field" (Rossi et al., 1999, p. 582). Experts were divided into two categories: theoreticians and practitioners. The theoreticians were individuals who were considered national leaders in academic social work. The practitioners were individuals who held positions in child welfare agencies and were considered reputable in the field. The worker group consisted of child welfare workers whose primary role was to investigate maltreatment. Each of the groups read vignettes and reported on their removal decisions.

Between the groups, workers were more likely to recommend custody than experts. Experts were more likely to utilize family preservation services than workers; however, workers were more likely to use traditional services or close cases with no services. Across both groups, being risk averse was positively associated with a decision to remove and asserting that case history was unimportant was negatively associated with the decision to remove. Additionally, the researchers found there was more variability within the worker group than within the expert group. Nevertheless, the researchers concluded the variance observed in both groups was high.

Traumatic Work Experiences

Regehr, LeBlanc, Shlonsky, and Bogo (2010) investigated the impact of work-related traumatic experiences, such as the death of a client, receipt of threats, or having been assaulted, of workers to understand how these experiences may influence decision making. Their sample included 96 child welfare workers in Canada. Participants were asked to complete a survey reporting whether they had experienced any of these traumatic events at work and if they felt distressed as a result. Most of the respondents (85%) reported experiencing at least one of the events at work. Of those who reported an incident, most (73%) indicated they experienced distress as a result.

The participants were then asked to interview and complete risk assessments on a simulated child welfare client. The researchers found an inverse relationship between levels of workplace trauma and risk score on one of the risk measures, meaning the more incidents workers had been exposed to, the lower the risk score. However, there was no relationship between incidents and risk score on two other risk measures scores. This study highlights that some types of experience, such as traumatic work events, can impact caseworkers' judgments of safety and risk and not all risk assessment tools are capable of systematizing the process enough to prevent unwanted variance.

Worker Perceptions

In the study by Graham et al. (2015) discussed above, the researchers also sought to understand workers' perceptions of organizational factors that influence decision making. The researchers found workers' perceptions of organizational support and workload manageability predicted decision making. Removal rates were lower for workers who indicated they experienced high levels of organizational support and for workers who perceived their workload as unmanageable. Regarding the latter finding, the authors noted this result is contradictory to the common belief that workers who do not have sufficient time to investigate will err on the side of child safety. Instead, they posited, it appears lack of time to investigate maltreatment results in more children remaining in their home when it may have been in their best interest to be removed and placed in a safer environment.

Additionally, Graham et al. (2015) investigated the influence of workers' level of perceived personal liability, that is, the degree to which they feel they will be supported by their agency versus held personally liable in the event of a negative situation. In their structural equation model, worrying about liability was impacted by other factors in the model, such as the amount of support the workers felt they had and if they reported feeling uncomfortable with difficult clients. However, perceived personal liability was not significantly related to removal rates. These results contrast with conclusions drawn by Dettlaff and Rycraft (2008) who found, in qualitative interviews, that workers who felt they would be held personally responsible for negative outcomes were more likely to report erring on the side of child safety. Nevertheless, Graham et al. (2015) noted conclusions drawn from the liability scale should be made cautiously because the internal consistency estimate of the scale was low.

Attitudes and Beliefs

Researchers have been interested in attitudes and beliefs about child safety and family preservation as a possible source of variance in judgments and decision making. Vignette studies found caseworker attitude toward removal does predict judgement (i.e., risk assessment), and removal decisions. Child safety or proremoval attitudes were related to higher risk ratings and increased removal recommendations (Benbenishty et al., 2015; Davidson-Arad & Benbenishty, 2010, 2016; Fluke et al., 2016). For example, Davidson-Arad and Benbenishty (2010) found proremoval attitudes were predictive of assigning higher risk assessment scores and of making recommendations for more intrusive child welfare interventions.

Davidson-Arad and Benbenishty (2016) found child welfare caseworkers tend to have different attitudes toward child welfare services than social work students. When compared to the students, child welfare caseworkers had a less favorable attitude toward removal, a more negative view of the quality of residential care, and they preferred more timely reunifications. Interestingly, they also found caseworkers' attitudes had the same size impact on their removal decisions as the students' attitudes did. This means caseworkers, who were presumably trained to make removal decisions based on case facts, were no more able to moderate their attitudes than students. The authors highlighted this finding as particularly enlightening and emphasized the need for more training to help professionals understand the impact of their attitudes and beliefs on their decision making.

Researchers have also explored the relationship between caseworker attitudes and beliefs toward child safety and family preservation with caseworkers' personal characteristics. Arad-Davidzon and Benbenishty (2008) surveyed child welfare workers in Israel on these attitudes and beliefs (Child Welfare Attitudes Questionnaire; Arad-Davidzon & Benbenishty, 2008). Using cluster analysis, two groups were identified, a proremoval (61%) and an antiremoval group (39%). Compared to the proremoval group, the antiremoval group was less likely to recommend removal of a child from their home, and more likely to support efforts to reunify. They were also unsupportive of longer stays out of the home, they recommended less intensive interventions, and they had more negative views of residential and foster care quality. Interestingly, group membership was not attributed to caseworker demographics, including gender, age, religion, and marital status, and professional characteristics, including education and experience.

Fluke et al. (2016) also used the Dalgleish Scale to assess caseworkers' attitudes and beliefs related to attitudes toward family preservation and child safety. They too found demographics, including gender, race, and ethnicity, were not predictive of worker attitudes. However, caseworker experience and caseworker role were significantly related to risk assessment scores and to removal decisions. Caseworkers with less experience were more oriented toward safety than family preservation. Caseworkers who carry cases, as opposed to staff who do not carry cases, were also more oriented toward safety than family preservation.

Process Influences

In addition to investigating the caseworker factors that influence decisions, researchers have studied how the processes used, such as confirmation bias and heuristics, influence investigations and decision making. After reviewing documentation of public inquiries (legal reviews) on child welfare cases that had particularly negative outcomes (e.g., child death, serious injury, etc.) in Britain, Munro (1998) concluded child welfare workers rely on their own common sense and do not have a theoretical understanding of their work. In other words, the case workers did not know what factors influence risk of re-abuse and evidence of effective interventions. Additionally, Munro indicated workers have difficulty articulating what processes they use when investigating.

In reviewing studies of investigative procedures, Bartelink et al. (2015) concluded child welfare workers attend more to verbal, as opposed to written, and emotionally salient information when making investigative judgments and decisions. For example, LeBlanc, Regehr, Shlonsky, and Bogo (2012) had workers interview an actress who portrayed a parent. They found the workers' stress response was higher when the parent was confrontational and the increased stress response was related to higher risk assessment scores on some, though not all, risk assessment tools.

Bartelink et al. (2015) concluded investigators make an early judgment about a case, which then biases the subsequent investigation. Investigators, they indicated, seek out confirmatory evidence and ignore contradictory evidence. As an example, in interviews with child welfare workers in New Zealand, Stanley (2013) found workers tended to make judgments on cases based on information reported by the referent (such as the police) and then seek out information in past case files to support that conclusion. Stanley concluded that risk judgments made early in the case precluded the workers from considering alternatives. Additionally, the workers "did not consider the extent to which [their] decisions, such as those to remove a child exposed families to other types of risk, to the potential harm of placing children in alternative or foster care" (p. 67). Confirmation bias was also found by Spratt, Devaney, and Hayes (2015) who had workers in Northern Ireland make removal decisions using vignettes.

Factors Influencing Disclosure Belief

Though evidence is limited, some researchers have found a relationship between having a history of abuse and judgment of a report of abuse. For example, Jackson and Nuttall (1994) administered a vignette to a sample of clinical social workers and instructed them to report the credibility of the allegations. The social workers also completed a survey disclosing their own history of physical and sexual abuse victimization. Females, younger social workers, and social workers with a history of trauma were more likely to indicate the reports of abuse were credible. Other studies have found similar results and it appears women are more likely to believe reports of sexual abuse than men (Cromer & Freyd, 2007, 2009; Cunningham & Cromer, 2016).

Findings on having a personal history of trauma and believing accounts of sex abuse are mixed. Cromer and Freyd (2007) found that having a history of trauma impacted whether an individual believed a report of sex abuse in a sample of college students. However, having a personal history of trauma interacted with gender. Women who had personal histories of trauma were equally likely to believe allegations of abuse as women who did not have such histories. However, men who had personal histories of trauma were more likely to believe allegations of abuse than men who did not have histories of trauma. Cromer and Freyd (2009) found college students with a personal history of trauma were more likely to believe reports of any types of abuse; no interaction with gender was found. However, in a similarly designed study with college students, Cunningham and Cromer (2016) found having a personal history of sexual victimization did not impact whether students believed a report of sex trafficking. These studies also found attitudes such as sexism and belief in rape and human trafficking myths are inversely related to believing reports of abuse (Cromer & Freyd, 2007, 2009; Cunningham & Cromer, 2016).

Limitations of the Studies

While researchers continue to make strides in understanding CPS caseworker decision making, there is a lack of consistent empirical evidence of factors that influence decisions to draw firm conclusions on the influence of caseworker factors on removal decisions. The disparate findings noted above are likely due to the newness of this field of investigation. Confounding variables have not been identified, there is a lack of agreed upon variable operationalization, and different methodologies all likely contribute to these discrepancies. The following is a critique of the studies above.

Confounding Variables

The DME framework postulates there are an extensive range of factors that influence decision making. Many of the decision-making studies discussed above have poor internal validity because other pertinent factors are not controlled for when investigating the influence of specific factors in the research designs. Accordingly, it is not clear which factors are important, under which circumstances, and to whom they are influential. The Graham et al. (2015) study highlights the importance of this understanding. The researchers found no direct relationship between removal and caseworker characteristics, including gender, years of experience, and attitudes. This relationship was mediated by other factors, including the caseworkers' average risk assessment score.

These findings led the researchers to conclude that while caseworker characteristics did not appear to predict removal decisions, they did influence judgment of risk and that it is possible that "risk assessment is adjusted to be more consistent with caseworkers' decisions" (Graham et al., 2015, p. 20). In other words, workers may score risk assessment tools to be consistent with the decisions they have made, rather than using the risk assessment tool as an objective measure from which to determine the need to remove a child. Accordingly, controlling for risk assessment score is masking the impact of those characteristics on decision making.

Variable Operationalization

The contrasting results may be a product of non-uniformity in the way the independent and dependent variables were operationalized. For example, the researchers who investigated the impact of attitudes and beliefs on decision making used different measures (Davidson-Arad & Benbenishty, 2016; Fluke et al., 2016; Graham et al., 2015). While the use of many instruments can be helpful, it is currently unknown if these tools are measuring the same constructs and it is difficult to draw conclusions about the impact of attitudes and beliefs on decision making. Similarly, as noted above, various instruments are used to assess the risk of future maltreatment (this is in addition to the problem stemming from low interrater reliability).

Methodologies

The studies reviewed above applied vignette designs, surveys tools, or analysis of administrative data. While each provides unique contributions, they also have inherent flaws. The following is a review of the contribution and limitations of each methodology.

Vignette Limitations

The use of vignettes has been criticized due the contrived nature of the presented case. Even if the vignette is modeled after real-world cases, the information must be pared down significantly and does not provide the rich detail a true investigation can provide (Arad-Davidzon & Benbenishty, 2008). The emotional impact on the worker may also be different in a vignette than in an actual case, as the worker did not meet a child and family, and they did not see, hear, or smell the impact of the abuse or neglect for themselves (López et al., 2015). Accordingly, it is unknown if the judgments and decisions made regarding the vignette correspond with reality (Britner & Mossler, 2002; Wason, Polonsky, & Hyman, 2002).

Vignettes are also susceptible to framing effects if not carefully worded (Wason et al., 2002). Specifically, individuals may be prone to providing different responses if information and questions are framed positively or negatively. For example, results may be impacted by framing effects if a vignette or question is worded “a 75% chance of no future abuse” versus “a 25% chance of re-abuse.”

Vignettes also provide many advantages as a research tool (Wason et al., 2002). They can be applied in experimental settings, where information contained can be manipulated by the researchers to best understand the impact of those differences. Vignettes provide researchers with the ability to understand how different individuals respond to standard stimuli. Vignettes can reduce social desirability bias, particularly when the responses are distanced by using third person language (Choong, Ho, & McDonald, 2002). Additionally, there are pragmatic advantages to the use of vignettes such as lower study costs and time investment, which can result in the ability to increase sample size.

Survey Limitations

Survey questionnaire research is frequently used to assess factors that impact judgment and decision making in child welfare (López et al., 2015). Achieving a representative sample is of utmost importance in survey research. Though ideal, it is rare to achieve random sampling in survey research, which is a major limitation of this approach (Shadish, Cook, & Campbell, 2002). The sampling frame is impacted by the availability of the population, method used to administer the survey (e.g., mail, internet, phone), language barriers, reading ability, and the willingness of the population to complete the survey (Trochim, 2006). Different methods have different advantages. For example, surveys administered over the internet are valuable for cost and coordination reasons, as well as the ability to reach individuals in a range of geographical areas. However, the sample is limited to individuals who have computer and internet access. Even if an ideal sample is reached, low response rates may lead to underrepresentation of individuals in a population and the survey responses will be biased if response was influenced by a systematic factor.

The length and content of surveys pose difficult quandaries for researchers (Trochim, 2006). Long or difficult surveys may cause respondents to leave items blank, provide random responses, or opt out. Short surveys, however, limit the amount of information researchers can ascertain. As such, survey content must be chosen carefully, balancing response rates with accurate and adequate information.

There are also problems with self-report data gathered in surveys (Ericsson & Simon, 1980; Trochim, 2006). Respondents may unknowingly respond in socially desirable ways or purposefully attempt to deceive (Trochim, 2006). There are certain types of information that we are unable to self-report due to problems in memory, processing ability, and perception; actual behavior may not correspond to the self-report information (Ericsson & Simon, 1980).

The instruments used in many child welfare decision-making studies are typically designed to measure demographic information, as well as measure a construct (e.g., attitudes toward or beliefs about removal). Classical test theory assumes an observed assessment tool score, *X*, is the sum of an individual's true score, *T*, plus some measurement error, *E* (Crocker & Algina, 1986). However, *T* and *E* are not observable; thus it is vital to explore the psychometric properties of the instruments used.

Reliability is defined as the ratio of a measure's true score variance to total variance (i.e., the proportion of variance that is not error; Crocker & Algina, 1986). If the ratio of true variance to total variance is high, meaning there is little error variance, the measure can be given multiple times and a similar observed score, *X*, would be expected. Conversely, if the proportion of error variance is high, the observed score would be highly variable. Reliability can be measured through the following methods: test-retest reliability, parallel forms reliability, internal reliability, split-half reliability, and interrater reliability.

The validation of an instrument is "the process by which a test developer or test user collects evidence to support the types of inferences that are to be drawn from the test scores" (Crocker & Algina, 1986, p. 217). There are three major types of validity: content validity, criterion validity, and construct validity (Crocker & Algina, 1986). Content validity concerns whether a test represents a general domain and if inferences can be drawn from a measure to the larger domain. Criterion validity measures how highly an instrument's results are related to actual behavior. Construct validity is how well an instrument measures what it was designed to measure.

Despite these limitations, survey research has many advantages (Trochim, 2006). Survey research enables researchers to measure traits that are not observable, such as attitudes or beliefs. As discussed above, surveys make it possible to gather information from a large group of participants, for potentially low cost, and with few resources required. Additionally, though social desirability is a concern, the anonymity of surveys allows for more honest reporting of information.

Analysis of Child Welfare Administrative Data

Child welfare administrative data have been used to investigate many research questions in child welfare; however, there are limitations to working with agency data (English, Brandford, & Coghlan, 2000). As with any large database, child welfare agency data include imprecise and missing data (Drake & Jonson-Reid, 1999). In addition to basic data entry errors, workers may not be reliable, both within and between workers, in the way they report and record information. Databases are created by child welfare agencies to help organize and track information within the agency. As such, the variables contained may be recorded in ways that enable investigators to answer certain research questions.

Due to the importance of child welfare data, federal legislation has been enacted and funding opportunities created to assist in standardizing state databases (English et al., 2000). These legislative pushes, funding incentives, and increase in available technology have allowed many states to build enhanced databases. Additionally, accountability, such as annual federal reporting requirements, have assisted in building agency data integrity overtime (Children's Bureau, n.d.; Dettlaff et al., 2015; English et al., 2000).

The use of child welfare administrative databases in research studies can be advantageous (English et al., 2000). They provide naturalistic data and outcomes that are not possible to achieve through experiments. Because of funding for standardized databases, many administrative databases in the US have standard variables. Accordingly, researchers can compare children, families, and workers nationally. Child welfare databases also provide researchers with the opportunity to observe longitudinal trends, such as placement rates over time, or cross-sectional snapshots of child welfare populations. Finally, these databases are large and provide sufficient numbers of cases required in complex statistical analyses.

Missing Methodologies

None of the CPS caseworker studies employed designs in which workers are observed in the process of actual decision making (e.g., naturalistic observations, structured checklists, real-time sampling, and think-aloud protocols). Studies of this nature will be imperative to understand if information gathered in vignettes and surveys correspond to actual decisions. They also enable researchers to gather information on procedures used during the investigation and in decision making.

Summary and Conclusions

Many decision-making theorists agree there are two systems individuals use to make decisions, a quick and unconscious process, known as System 1, and a slower analytic process, known as System 2 (Fazio, 1990; Kahneman, 2003; Petty & Cacioppo, 1986; Stanovich & West, 2000). It is unknown which system caseworkers use when making removal decisions. It is possible, for example, that caseworkers rely on System 1 heuristics when they very busy or if they have a lower tendency to use analytic thought.

It also possible caseworkers primarily use System 2 to make removal decisions. Research suggests that when there is sufficient time to make decisions, cognitive ability to make decisions, and high motivation to make the best choices, decisions will be made in System 2 (Fazio, 1990; Stanovich & West, 2000; Tversky & Kahneman, 1974). Accordingly, it is possible removal decisions are made in the more analytic and deliberate System 2. Though there are times when workers have limited time to assess safety and risk, such as when there is imminent danger, the majority of cases referred to DCFS are priority three cases where the worker has 3 days to initiate contact with a child and 30 days to complete the investigation (DCFS, 2010). Therefore, caseworkers are not limited in their time to make a judgment such that they would be forced to use System 1. Additionally, workers have been trained on agency practice and should have the cognitive ability and access to resources to conduct the necessary judgements. Finally, given that the potential outcome of their decision could result in a serious situation, such as inflicting further trauma on a child and family through removal or further maltreatment if a child is left in a home, motivation should be high for caseworkers to use the more deliberate analytic process of System 2.

It is also possible that caseworkers use heuristics more deliberately in System 2 (Frederick, 2002). This is important because accurate and timely feedback on the outcomes of choices is necessary to develop expertise and accurate heuristics (Kahneman & Klein, 2009). To do this, CPS caseworkers would need to receive feedback on the long-term outcomes of the cases, such as whether there were new incidents of abuse or neglect, after controlling for other factors that influence outcomes, such as treatment. However, this is not currently standard practice in child welfare agencies (Drake &

Washeck, 1998), possibly due to the complicated nature of such a task and lack of tested methods for providing such feedback.

If decisions are made in System 2 and there is a lack of accurate feedback necessary to develop expertise, it is imperative to explore what is shaping caseworker decision-making behavior. Case factors are often predictive of removal decisions. Some factors justifiably predict removal decisions, such as characteristics of the maltreatment (Rossi et al., 1999; Stokes & Taylor, 2014), families' current circumstances (Rossi et al., 1999), and risk assessment scores (Graham et al., 2015; Rivaux et al., 2008). However, as discussed above, there is some question as to whether caseworkers are completing risk tools in a manner that supports their preconceived decisions.

Other case factors also predict removal, but it is unclear if those factors should be associated with removal or are a result of bias. For example, children's race and ethnicity have been found to predict removal decisions (Baumann et al., 2010; Dettlaff & Rycraft, 2008; Fallon et al., 2013; Graham et al., 2015; Rivaux et al., 2008; Wulczyn & Lery, 2007). These findings may represent biases in removal decisions; however, researchers have also found the effect for race and ethnicity disappears after controlling for socioeconomic status (Dettlaff et al., 2011). This finding has led some researchers to conclude minority youth are not disproportionately removed, but are disproportionately affected by adverse socioeconomic circumstances that increase the risk of maltreatment (Bartholet, 2009; Drake et al., 2011; Fluke et al., 2003).

When comparing decisions across countries and states, research findings suggest there are differences between agencies that contribute to differential decision making (Benbenishty et al., 2015; Rossi et al., 1999). However, at present, it is not known what causes these differences. With regard to external influences, researchers have posited the availability of services is related to decisions to remove (Dettlaff & Rycraft, 2008; Fluke et al., 2010; Font & Maguire-Jack, 2015) and that legal partners may attend to different information when making decisions (Britner & Mossler, 2002).

Regarding caseworker factors, evidence suggests caseworker characteristics, such as gender and education, do not predict removal decisions (Font & Maguire-Jack, 2015; Graham et al., 2015); however, there are mixed findings regarding the influence of years of experience with DCFS (Brunnberg & Pećnik, 2007; Davidson-Arad et al., 2003; Font & Maguire-Jack, 2015). Emerging evidence suggests caseworkers' perceptions of their workload and agency support (Graham et al., 2015), experiencing work-related traumatic experiences (Regehr et al., 2010), and stress response related to confrontational clients (LeBlanc et al., 2012) can all influence risk assessment and removal decisions.

General research on decision making suggests attitudes can influence decisions at multiple points in the decision-making process (Sanbonmatsu et al., 2005). In the context of child welfare, vignette studies have found attitudes toward child safety and family preservation influence removal decisions (Arad-Davidzon & Benbenishty, 2008; Benbenishty et al., 2015; Davidson-Arad & Benbenishty, 2010, 2016; Gold et al., 2001). Though a direct link has not been made between having a childhood history of adverse experiences and decision making, studies have found having a personal history of trauma may impact judgment of allegations of abuse (Cromer & Freyd, 2007, 2009; Jackson & Nuttall, 1994).

Study Purpose

There is considerable unexplained variance in CPS caseworkers' decisions to remove children from their homes (Dettlaff et al., 2015; Fluke et al., 2014; Rossi et al., 1999). This variance is beyond variance expected due to child and family risk factors. Variance that is attributable to caseworker factors is undesired because this means decisions are not made systematically; removal decisions may differ for children and families simply as a result of being assigned to different caseworkers. Few studies have investigated how caseworker factors impact these decisions (Arad-Davidzon & Benbenishty, 2008; Benbenishty et al., 2015; Davidson-Arad & Benbenishty, 2010, 2016; Gold et al., 2001; Graham et al., 2015). Of those studies, only one used real-world child welfare data and the remaining studies explored the impact of those factors on decisions made in vignette studies.

The present study explored if caseworker factors predict decisions to remove children from their homes using real-world data from a statewide child welfare population. Caseworker factors included the caseworkers' minority status, gender, years of experience, attitudes toward child safety and family preservation, and childhood history of adverse experiences. To explore the influence of caseworker factors, I first determined if the region in which the case was investigated and case characteristics predicted removal decisions to control for that variance. Case characteristics included the child's age, gender, race and ethnicity, and number of prior supported investigations in which the child was involved.

The purpose of this research was not to identify ideal CPS removals, meaning the focus is not on detecting situations in which children should remain in their homes or be placed into out-of-home care. Ideal removal situations should be determined by child welfare agencies (Mansell, 2006). Instead, as indicated above, the purpose was to investigate if caseworker factors influence removal decisions.

The findings from this study contribute to the growing body of empirical data on CPS decision making by exploring the influence of caseworker factors. The results can be used to further child welfare decision-making theories and frameworks, such as the DME. Additionally, the findings can be used to inform and create policy and interventions to reduce unwanted variance and help ensure consistent decisions are made for children and families who come into contact with child welfare systems.

Research Questions

My research explored whether caseworker factors influence removal decisions. Specifically, I investigated the following research questions (RQ):

RQ1: Do caseworker factors predict removal decisions?

RQ2: Do caseworker attitudes and beliefs toward child safety and family preservation predict removal decisions?

RQ3: Does a worker's childhood history of adverse events predict removal decisions?

RQ4. Do any of the survey scales, two measuring self-reported attitudes and beliefs towards child safety and family preservation and one measuring childhood history of adverse events, have predictive ability beyond the others?

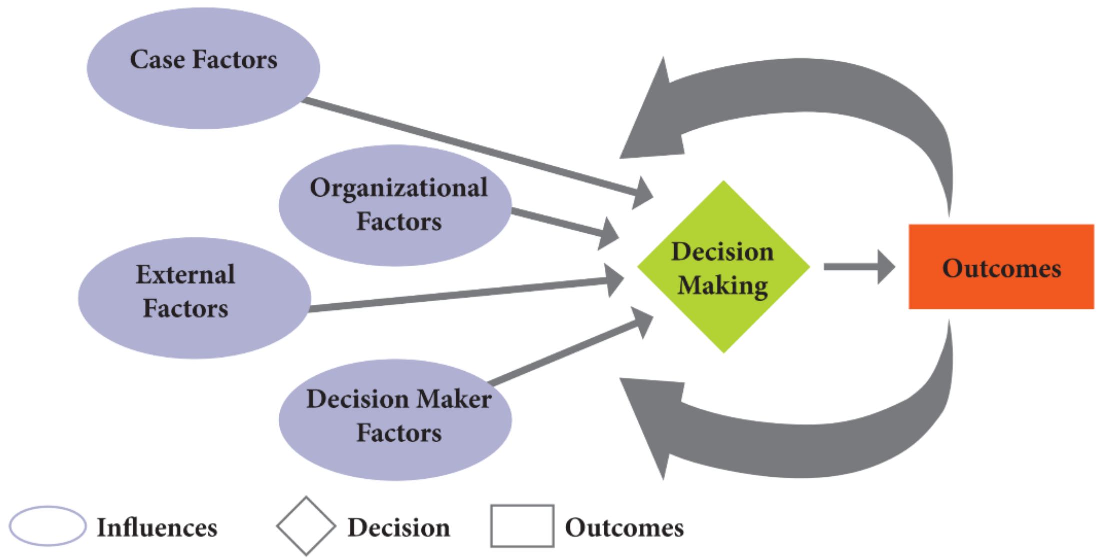

Figure 2.1 The Decision-Making Ecology (Fluke et al., 2014)

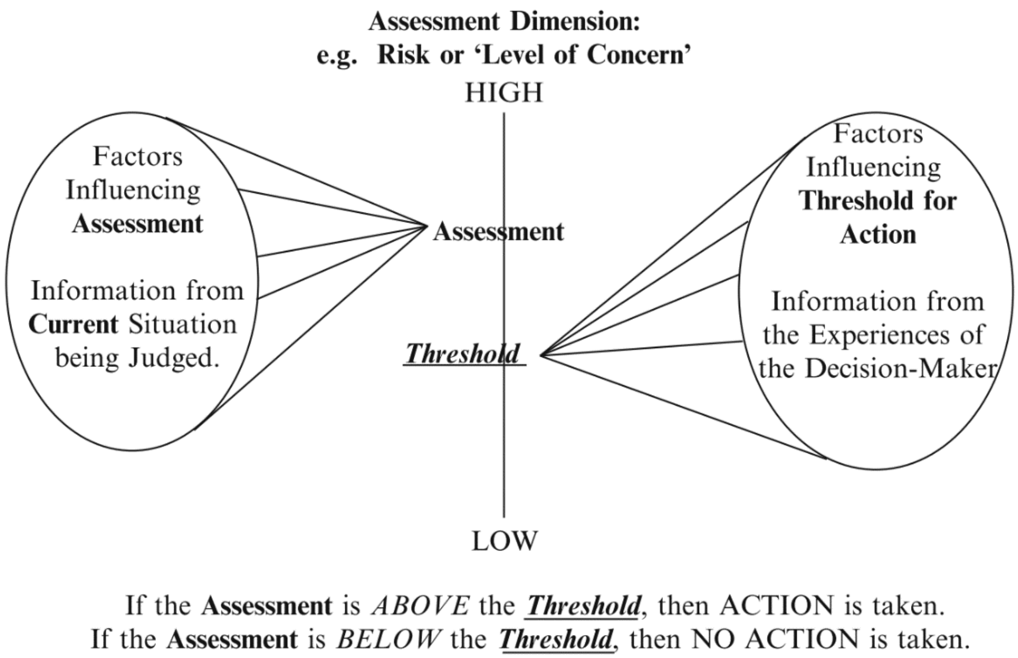

Figure 2.2 The General Assessment and Decision-Making Model (Fluke et al., 2014)

CHAPTER 3

METHODOLOGY

Research Design

This study explored whether caseworker factors predict decisions to remove children from their homes. Caseworker factors included the caseworkers' gender, minority status, ethnicity correspondence between the caseworker and child, years of experience with DCFS, attitudes toward child safety and family preservation, and childhood history of adverse events. To explore the influence of caseworker factors, it was first determined if there was a need to control for the region in which the case was investigated and case characteristics. Case characteristics included the child's age, gender, race and ethnicity, and number of previous supported investigations in which the child was involved. These analyses were conducted using data from a statewide child welfare population using cross-classified logistic multilevel modeling.

It is important to note that though variables are referred to as case, organizational, and caseworker factors or characteristics, they were not necessarily entered at those levels in the models. The terminology case, organizational, and caseworker is used to align this research with the DME framework's organization of decision influences. This differs from the analysis levels of child case, family, and caseworker used in this study. For example, tenure is a caseworker factor. However, these data include cases caseworkers have investigated over time. Therefore, tenure was calculated and entered into the model at the child-case level.

These analyses were conducted using survey data collected during an evaluation of the effectiveness of a Utah's IV-E Waiver Demonstration Project, DCFS's statewide intervention program aimed at reducing the need of out-of-home placements (for more information on Utah's IV-E Waiver Demonstration Project, see DCFS, 2016). The use of these secondary data was advantageous because access to statewide caseworker survey data is rare and difficult to have approved, due to the time imposition on the caseworkers. Additionally, there is investment on behalf of Utah's child welfare system to answer these research questions.

Four samples were included in this study. The first sample was comprised of the overall dataset from DCFS's child tracking administrative database. Samples two, three, and four included subsets from the first sample that were linked to caseworker survey responses. Each sample is described in the following sections. All sample sizes reported below include only cases with complete data.

Participants

CPS Sample

The first sample was the CPS Sample and was comprised of datasets from Department of Human Services (DHS) human resources data and Utah's DCFS administrative database. The DCFS administrative database dataset included all supported CPS cases with a start date between October 1, 2008 and July 31, 2016, as well as all caseworkers who were employed with DCFS during the same time period.

Supported cases are cases where the CPS investigator found the allegations of abuse had merit. There were 77,173 child cases, 36,731 families, and 516 caseworkers in this sample.

Attitudes Sample

The second sample is the Attitudes Sample. All caseworkers who were assigned CPS cases between May 2015 and April 2016 ($N = 224$) were recruited to complete two online surveys that explored their attitudes and beliefs toward child safety and family preservation. This is the same population from which the third and fourth samples, described below, was recruited. However, because the data were collected on different days and a separate set of caseworkers responded, these were considered to be different samples. There were 33,745 child cases, 17,185 families, and 191 caseworkers in this sample.

Adverse Childhood Events Sample

The third sample is the Adverse Childhood Events (ACE) Sample. As with the Attitudes Sample, all caseworkers who were assigned a CPS cases between May 2015 and April 2016 ($N = 224$) were recruited to complete the Adverse Childhood Events survey. There were 21,239 child cases, 12,131 families, and 143 caseworkers in this sample.

Combined Sample

The fourth sample is the Combined Sample. This sample included all caseworkers who completed the two attitudes and beliefs surveys and the Adverse Childhood Events survey. There were 20,405 child cases, 11,608 families, and 134 caseworkers in this sample.

Data Sources

The following is a description of the variables that were used in this study, listed by database source. The same variables were used across samples and research questions, except for caseworker gender, which will be discussed below.

Human Resources Data

This study used human resources data for caseworkers who were employed with DCFS between October 1, 2008 and July 31, 2016. Human resources data include the caseworkers' gender, race, ethnicity, and the date they were first entered as a user in the DCFS database.

Gender

Though the variable gender was included in this dataset, gender was missing for 38% of this sample. Therefore, gender was not included as a variable in this sample. Because of this issue, information on the caseworkers' gender was collected during survey administration and gender was included as a variable in the samples 2, 3, and 4.

Race and Ethnicity

Variables for the workers' race and ethnicity were provided in this dataset. The majority of caseworkers in this sample, approximately 90%, were Caucasian. Therefore, the caseworkers' race and ethnicity was coded as minority or nonminority.

Years of Experience With DCFS

The date the caseworker was entered into the DCFS agency database as a user was used as a proxy for the DCFS hire date. The caseworker's years of experience with DCFS was created at a case level by calculating the number of years between the caseworkers' hire date and the start date of the CPS case. Years of experience with DCFS represents the years of experience with DCFS, not necessarily as a CPS caseworker.

Administrative Data

These analyses included administrative data obtained from the DCFS agency database for all supported CPS cases that had a case start date between October 1, 2008 and July 31, 2016; this includes the 5-year period prior to the implementation of Utah's IV-E Waiver. This dataset included the case identification number (case ID), the child identification number (child ID), the CPS case start and end date, number of times the child was involved in a supported CPS investigation, foster care start date (if applicable), the child's age, the child's gender, and the child's race and ethnicity.

CPS Caseworkers

In Utah's database, there was no identification for job type. That is, the database does not differentiate between a CPS investigator and a foster care caseworker. CPS caseworkers are identified by the types of cases that are assigned to them. In this study, the variable caseworkers refers to the CPS investigators who were assigned as the primary caseworker during the CPS investigation.

Cases, Children, and Child-Cases

In this study, a case was defined as a unique CPS investigation of abuse. Cases may involve multiple children and there is always one primary caseworker assigned to each unique case. Children are unique children identified by a child ID. Children can appear multiple times in this dataset if they were involved in more than one CPS investigation. Because cases may have multiple children assigned to them and children can appear multiple times if involved in more than one investigation, the variable child case was used. A child case is a unique child ID and case ID combination.

Family

Children on the same case are expected to share some variance in their reasons for removal. Additionally, it is expected that children have similar reasons for removal as other children with whom they share cases. For example, if child A shared a case with child B and child B shared a case with child C, it is expected that child A and child C will have shared variance that should be accounted for in these analyses. To account for this systematic variance, a family variable was created. A family is defined as any children who share cases and the children with whom any of those children share cases.

Previous Supported Investigations

The variable previous supported investigations was a count of the number of times the child was involved in a supported CPS investigation. Supported investigations are when the CPS investigator finds sufficient evidence to conclude an allegation of abuse has merit.

The variables child age and number of previous supported investigations was used as a proxy for risk of future maltreatment. These variables have been shown to be significantly related to removal in previous investigations with this population (Social Research Institute, 2016). These variables were used instead of risk assessment score because the caseworker both completes the assessment of risk and makes the removal decision. Therefore, using the risk assessment score to control for risk could mask the relationship between these predictors and the decision. Though this is unconventional in decision-making research, as discussed above, Graham et al. (2015) found risk assessment fully mediated the relationship between caseworker characteristics and removal decision and concluded workers may be adjusting their risk assessments to support their removal decision.

Region

The region is the geographical area where case was assigned. Caseworkers can work in different regions over time and these data span a lengthy time period and, as a result, caseworkers cannot be nested within regions. Therefore, region was entered as a case-level predictor. There are five regions in Utah's child welfare system: Northern, Salt Lake Valley, Western, Eastern, and Southwest.

Removal

Removal is the dependent variable in the primary analyses. A removal occurs when a child is removed from his or her home and placed into foster care during a CPS maltreatment investigation. In this dataset, the child is considered to be removed when a foster care case is opened for a specific child-case between the CPS case-start and CPS case-end date.

Measures

CPS Cases Sample

No surveys were administered to this sample.

Attitudes Sample

Two survey scales were administered to this sample to measure the caseworkers' attitudes toward safety and family preservation. The following is a description of these variables and scales.

Demographics

Demographics were collected from human resources data, discussed above. However, because gender is known to be missing for many workers in the agency database, the workers were asked to report their gender before beginning this survey.

Dalgleish Scale

The first scale is the Dalgleish scale (see Appendix E; Dalgleish, 2010; Fluke et al., 2016). This tool was also designed to measure attitudes toward child safety and family preservation. This scale consisted of eight sentence pairs. Each pair included a sentence leaning toward child safety and a sentence leaning toward family preservation. For example, one pair included the following two statements: “The client is the child and all other work is secondary” and “Work should be focused on keeping the family together.” These were forced choice items where the participants were asked to choose the statement that best reflects their general work focus and beliefs. The participants were then asked to rate their strength of preference for the statement they chose on a five-point Likert scale, ranging from very weak to very strong. In this example, a participant may choose sentence A as the statement that best reflects his or her general work focus and beliefs and rate the strength of their preference as weak. Some of the statements were repeated on the scale, but were paired with different statements each time.

This scale is scored by assigning a -1 for items that were oriented toward family preservation and a +1 for items oriented toward child safety. That score is then multiplied by the strength of preference for that item. In the above example, sentence A is oriented toward child safety and is scored a +1. This is then multiplied by their strength of preference, a 2, and the final score for that item pairing is +2. Item pair scores were averaged if at least six items were completed by the participant to create the final score. The range of scores is -5 to +5. A low score reflects attitudes more favorable toward family preservation and a high score reflects attitudes more favorable toward child safety.

This scale was recently used to investigate if CPS caseworkers' attitudes are predicted by their demographics and job experience (Fluke et al., 2016). A Cronbach's alpha of .66 was reported in that study. The internal consistency for the eight items on the Attitudes Sample and Combined Sample were low, $\alpha = .57$ and $\alpha = .52$, respectively.

Against Removal From Home of Children at Risk Scale

The second scale was the Against Removal from Home of Children at Risk Scale (see Appendix D; Arad-Davidzon & Benbenishty, 2008). For simplicity, this survey is referred to as the Against Removal scale from here forward. The authors described this scale as measuring attitudes toward child safety and family preservation. Items are geared as assessing whether the caseworker believes "children should be removed from homes where their parents abuse them physically, sexually, or emotionally, and when they neglect them, and by other items stating that efforts should be made to keep the children at home despite these abuses" (Arad-Davidzon & Benbenishty, 2008, p. 112).

This scale also contained three items related to the workers' feelings about reunification. These questions ask whether they agree reunification efforts should be made under any abuse circumstances and, more specifically, when a child has been neglected or emotionally abused. Finally, two of the items measured the caseworkers' beliefs regarding involvement of the child and family in removal decisions.

This scale had nine items that were rated on a seven-point Likert scale, ranging from strongly agree to strongly disagree, two of which were reverse scored. This scale was scored by averaging the item scores if at least seven items were completed. The range of possible scores was one to seven. A low score reflects attitudes more favorable toward family preservation and a high score reflects attitudes more favorable toward child safety.

This scale has been used in several studies and has been found to be a significant predictor of caseworkers' removal decisions in vignette studies (Arad-Davidzon & Benbenishty, 2008; Benbenishty et al., 2015; Davidson-Arad & Benbenishty, 2010, 2016; Gold et al., 2001). This scale has been shown to have acceptable psychometric properties; the researchers reported a Cronbach's alpha of .80 (Arad-Davidzon & Benbenishty, 2008; Davidson-Arad & Benbenishty, 2010). The internal consistency for the eight items on the Attitudes Sample and Combined Sample were acceptable, $\alpha = .71$ and $\alpha = .74$, respectively.

ACE Sample

The Adverse Childhood Experiences (ACE) survey was also administered to caseworkers. This survey was an adapted version of a survey designed by Felitti et al. (1998) as part of the Adverse Childhood Experiences study. The authors indicated the ACE survey was designed with the purpose of gathering data on the prevalence of traumatic or adverse childhood experiences, including psychological maltreatment, physical abuse, sexual abuse, violence against a child's mother, having lived with substance abusers or mentally ill persons, and having family members who were incarcerated.

This tool has been adapted by many researchers. The version used in the present study was created by the CDC; Centers for Disease Control and Prevention (2010) and is an abbreviated version of the original survey (see Appendix F). This survey is broken down into two major categories: abuse and household challenges. The category of abuse is further broken in into the following subcategories: emotional abuse, physical abuse, and sexual abuse. The category of household challenges is broken in into the following subcategories: intimate partner violence, household substance abuse, household mental illness, parental separation or divorce, and incarcerated family member. Additionally, the original item about the abuse of a child's mother has been modified to assess whether either parent has been involved in intimate partner violence. Each subcategory has one item on this survey with the exceptions of household substance abuse, which has two items, and sexual abuse, which has three items. Commensurate with the CDC scoring, scores was categorized into the following groups: 0 ACEs, 1 ACE, 2 ACEs, 3 ACEs, 4 or more.

Combined Sample

This sample includes the three surveys described above: Against Removal scale, Dalgleish scale, and ACE survey.

Procedure

As indicated above, these data and surveys were previously collected as part of Utah's IV-E Waiver Demonstration Project Evaluation and were analyzed as secondary data. The following is a description of the procedures that were involved in the data collection and survey administration.

CPS Sample

All data were provided by DCFS.

Attitudes Sample, ACE Sample, and Combined Sample

Participants were recruited to complete online surveys. To reduce burden on caseworkers and increase the likelihood of participation in the surveys, the survey scales were administered over 3 weeks in May 2016. The Against Removal and the Dalgleish Survey were administered beginning May 9, 2016. The Adverse Childhood Experiences Survey was administered beginning May 23, 2016. The surveys were closed June 3, 2016.

Prior to survey administration, the participants received an email from the director of Utah's DCFS. This email informed the caseworkers of the upcoming surveys, explained the purpose of the surveys, and encouraged their participation (see Appendix A). On the date of the survey administration, the caseworkers received an automated email from the online survey system inviting them to participate in the survey. The email included a brief explanation of why they were selected to participate in the survey, the reason for the study, and information explaining that they would be asked to participate in surveys over several weeks (see Appendices B-C). The automated survey system sent two additional reminder emails if the caseworker did not complete the surveys. These survey data were linked to the participants' human resources data and the DCFS administrative data.

Protection of Human Rights

The Institutional Review Board of the University of Utah approved this study (IRB_00064471; see Appendix G). This study was also approved by the Institutional Review Board of the Department of Human Services (IRB 0531; see Appendix H). DCFS staff participating in the survey were consented in the online survey systems prior to beginning the survey (see Appendix I). Consent was waived to access human resources and administrative data by both IRBs.

Analyses

The primary analyses for these data were cross-classified logistic multilevel models and logistic multilevel models conducted in R using the lme4 package, version 1.1-12 (Bates, Maechler, Bolker, & Walker, 2015). Cross-classified logistic multilevel models were required for these data for several reasons. Multilevel models allow for data that are nested within higher-level units (Baldwin, Wampold, & Imel, 2007; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999). As such, these data cannot meet the assumptions of independence and uncorrelated errors made in other analyses. These models also allow data to be cross-classified into the higher levels (Raudenbush & Bryk, 2002). These data are cross-classified because children are nested within caseworkers and families. These nestings are not a hierarchical structure because families can have multiple caseworkers assigned to them and caseworkers can work across families.

Multilevel models are also advantageous because caseworkers can be considered random factors (Baldwin et al., 2007; Raudenbush & Bryk, 2002). Modeling an effect as a random effect assumes the units in a study are random and represent a larger universe of units. This means conclusions about the effect can be generalized to a larger population. In this study the caseworkers were assumed to be a sample of a possible universe of caseworkers. Martindale (1978) and Baldwin et al. (2007) highlighted that the goal of the psychotherapy research is to generalize findings not only to all possible clients, but also to all possible therapists. This too should be the goal of child welfare decision-making research. As such, these models will be used to allow caseworkers to be modeled as random factors.

Multilevel models are robust and allow for complicated models with unbalanced data (Baldwin et al., 2007; Raudenbush & Bryk, 2002). These models allow the researcher to include both within- and between-caseworker predictors concurrently. For example, child case level predictors can be included as a within caseworker predictor and caseworker attitudes can be included as a between caseworker predictor in the same model. Additionally, the groupings in multilevel models can be unbalanced, or have unequal sample sizes. This was necessary in these analyses because the caseworkers have not worked an equal number of cases. Similarly, families do not contain equal numbers of child cases.

Centering

It is important to understand the impact of centering variables within multilevel models. Variables can be centered though different methods, including centering around the grand mean (CGM), and centering around the group mean, referred to as centering within cluster (CWC; Enders & Tofighi, 2007). CGM involves subtracting the grand mean from each data point, x_{ij}- $\bar{x}$. CWC involves calculating the mean for each higher-level grouping and subtracting the group mean from each data point, x_{ij}- $\bar{x}_j$.

As with linear regression, centering changes the meaning of the intercept in a model (Enders & Tofighi, 2007). When variables are entered in their raw metric, the intercept is the predicted level of Y when all other variables are held constant at 0; the value of 0 may or may not be meaningful in the raw metric. However, when variables are centered at their means, the intercept becomes the predicted level of Y at the mean of the predictor variable. For example, if the variable child age is entered into a model, the intercept represents the odds of removal for a child who is 0. If the variable is CGM, the grand mean, or the average age of all of the child cases, is subtracted from the age of each child case, AGE_{ij}- $\bar{x}_{AGE}$. The intercept then represents the log odds of removal for the average-aged child and all coefficients are interpreted at the average of all other coefficients.

The same interpretation is applicable to dummy coded variables (Enders & Tofighi, 2007). When variables are coded 0-1, the interpretation of any fixed effects is for the group coded 0. For example, race and ethnicity is dummy coded with Caucasian as the reference group, any interpretation of level 2 fixed effects is for Caucasian youth. However, if the dummy codes are centered, the dummy code is interpreted as a proportion, or a weighted average.

Centering can also be used to partition the within and between level variance (Enders & Tofighi, 2007). For example, in this study the variance for years of experience was partitioned so that the within person variance is at level 1 and the between person variance is at level 2. This means that at level 1, the variance represents removal decisions as an individual caseworker gains more years of experience. At level 2, the variance represents how removal decisions are different between caseworkers with different average years of experience.

Variance can be partitioned using the two centering methods discussed (Enders & Tofighi, 2007). Scores can be CGM at level 1 and the means for each group aggregated and entered at level 2. While CGM means level 1 includes a mix of both between and within group variance, entering the means at level 2 creates two orthogonal variables. CWC at level 1 has the same effect and is algebraically equivalent to CGM. However, CGM with group means at level 2 creates the ability to assess not only whether there is a difference between the between and within group variance, but also to assess if the between group predictor at level 2 is different than zero.

The region in which the CPS case was investigated and each of the child case variables were entered at level 1 of each model. Each of these level 1 predictors, including dummy coded variables, were CGM. CGM was chosen partly to reduce non-essential multicollinearity in the models. This means, however, that each of the variables contains a mix of within and between caseworker variance. As such, the coefficients are uninterpretable.

Research Questions and Analysis Steps

Research Question One

The first research question is: Do caseworker factors predict removal decisions? This question was applied to the CPS Sample and answered in four primary analytic steps.

RQ1 Step 1

The first step was to calculate the variance components at the family- and caseworker-level. To do this a null, or unconditional, model was created where child cases were cross-classified within families and caseworkers. These models are referred to as unconditional models because they do not include predictors. They do, however, include random effects for the higher-level units which can be used to calculate the percent of variance at those levels. This model included random effects for the higher-level units family and caseworker. Conducting a random effects analysis is similar to conducting an ANOVA in that it indicates if the groups means are best explained by an overall mean, the grand mean, or by each groups' mean and the variance is partitioned to the within and between group components. This model was specified as follows (Raudenbush & Bryk, 2002, p. 377):

Level 1 (child case-level, or within-cell model):

$$\eta_{ijk} = \pi_{0jk}, \tag{3.1}$$

where

η_{ijk} is the is the predicted log odds of removal of child i, in family j, in caseworker k; and

π_{0jk} is the mean predicted removal for children in cell jk, meaning children who are in family j and assigned to caseworker k.

Level 2 (family- and caseworker-level, or the between-cell model):

$$\pi_{0jk} = \theta_0 + b_{00j} + c_{00k} + d_{0jk}, \tag{3.2}$$

where

π_{0jk} is the mean predicted removal for children in cell *jk*, meaning children who are in family *j* and assigned to caseworker *k*,

θ_0 is the average predicted removal for all child-cases,

b_{00j} is the random main effect for family *j*, meaning the contribution of family *j* averaged across caseworkers,

c_{00k} is the random main effect for caseworker *k*, meaning the contribution of caseworker *k* averaged across family, and

d_{0jk} is the random interaction effect, that is, the deviation of the cell mean from that predicted by the grand mean and the two main effects.

These two-level models can be written as a single mixed-model by substituting the level 2 model, or the between-cell model, into the within-cell model, or the level 1 model:

$$\eta_{ijk} = \theta_0 + b_{00j} + c_{00k} + d_{0jk}. \tag{3.3}$$

Binary variables are assumed to have a Bernoulli distribution (Raudenbush & Bryk, 2002). As such, in multilevel models with a bivariate outcome the predicted value of the outcome must be transformed to the Bernoulli distribution using a link function that constrains the values to fall between 0 and 1 (the actual possible range of the outcome). This transformation was done using the logit link function (Raudenbush & Bryk, 2002):

$$\eta_{ijk} = \log\left(\frac{\varphi_{ijk}}{1-\varphi_{ijk}}\right), \tag{3.4}$$

where

φ_{ijk} is the predicted probability of removal,

$\varphi_{ijk}/(1 - \varphi_{ijk})$ is the predicted odds of removal, and

η_{ijk} is the predicted logit of the probability of removal, or the predicted natural log odds of removal.

Therefore, substituting Equation 3.4 into Equation 3.3, the final model is:

$$\log\left(\frac{\varphi_{ijk}}{1-\varphi_{ijk}}\right) = \theta_0 + b_{00j} + c_{00k} + d_{0jk}. \tag{3.5}$$

For simplicity, all models from here forward will be presented in mixed-model form.

In cross-classified models, variance can be calculated between families, between caseworkers, and as residual variance (Raudenbush & Bryk, 2002). It is noted that in logistic models, the residual at level 1 is fixed and has a variance of $\pi^2/3$ (Hedeker, 2008). These intraclass correlation coefficients (ICC) are calculated as follows:

a) the ICC between two child-cases within the same family unit and assigned to the same caseworker:

$$\text{corr}(\eta_{ijk}, \eta_{i'jk}) = \rho_{bcd} = \frac{\tau_{b00} + \tau_{c00} + \tau_{d00}}{\tau_{b00} + \tau_{c00} + \tau_{d00} + \frac{\pi^2}{3}}, \tag{3.6}$$

b) the ICC for two child-cases in the same family unit but have different caseworkers:

$$\text{corr}(\ \eta_{ijk}, \eta_{i'jk'}\ ) = \rho_{bcd} = \frac{\tau_{b00}}{\tau_{b00}+\tau_{c00}+\ \tau_{d00}+\ \frac{\pi^2}{3}}\text{, and} \tag{3.7}$$

c) the ICC for two child-cases that have the same caseworker but different family units:

$$\text{corr}(\ \eta_{ijk}, \eta_{i'j'k}\ ) = \rho_{bcd} = \frac{\tau_{c00}}{\tau_{b00}+\tau_{c00}+\ \tau_{d00}+\ \frac{\pi^2}{3}}; \tag{3.8}$$

where

τ_{b00} is the family variance,

τ_{c00} is the caseworker variance, and

τ_{d00} is the residual variance at level 2.

RQ1 Step 2

The second step was to calculate the bivariate relationships between the region where the case was investigated and the case characteristics child age, gender, race and ethnicity, and number of previous supported investigations with removal decision. This was done by adding predictors into the model individually.

The models were as follows for the within-cell, or level 1, predictors:

$$\text{Log}\left(\frac{\varphi_{ijk}}{1-\varphi_{ijk}}\right) = \ \theta_0 + \pi_{1jk}a_{ijk} +\ b_{00j} +\ c_{00k} +\ d_{0jk}, \tag{3.9}$$

where

π_{1jk} is the generic term for a within-cell, or level 1, fixed effect and

a_{ijk} is the value for individual *i*, in family *j*, with caseworker *k*.

The model with predictors at level 1 and 2:

$$\log\left(\frac{\varphi_{ijk}}{1-\varphi_{ijk}}\right) = \theta_0 + \beta_{01k}X_k + \pi_{1jk}a_{ijk} + b_{00j} + c_{00k} + d_{0jk}, \qquad (3.10)$$

where

β_{01k} is the generic term for a between-cell, or level 2 fixed effect and

X_k is the value for caseworker *k*.

a) Region: dummy codes were created with the largest region, Salt Lake Valley Region, coded as the reference group. The dummy codes were grand mean centered and entered at level 1 (see Equation 3.9).
b) Child age: was grand mean centered and entered at level 1 (see Equation 3.9).
c) Child gender: was coded 0 - 1 (0 = female and 1= male), grand mean centered, and entered at level 1 (see Equation 3.9).
d) Child ethnicity: dummy codes were created with the largest group, non-Hispanic Caucasian, coded as the reference group, grand mean centered, and entered at level 1 (see Equation 3.9).
e) Number of previous supported investigations: Because this is a count variable, the linearity of the predictor and the log of the outcome was explored (Hosmer & Lemeshow, 1989). Results indicated a need to transform the number of priors by taking the cube root of the variable. The cube root of number of previous

supported investigations was entered at level 1 (see Equation 3.9)

RQ1 Step 3

The third step was to calculate the bivariate relationships between the caseworker factors years of experience, caseworker minority status, and correspondence between the caseworker's and child's ethnicity with removal decision. This was done by adding predictors into the model individually. The models were run as follows:

a) Caseworkers' years of experience with DCFS: The variance for caseworkers' years of experiences with DCFS was partitioned so that level 1 variance represented the within caseworker variance and level 2 was the between worker variance. This was done by CGM at level 1 and caseworkers' mean years of experiences were aggregated to level 2 and CGM (see Equations 3.9 and 3.10). In addition to centering, these variable were transformed into *z*-scores using the grand standard deviation (SD) for model specification reasons. This means a one unit change for years of experience with DCFS is one SD.
b) Caseworker minority status: was coded 0 - 1 (0 = nonminority and 1= minority), CGM, and entered at level 2 (see Equation 3.10).
c) Ethnicity correspondence: was coded 0 - 1 (0 = no correspondence and 1= correspondence), CGM, and entered at level 2 (see Equation 3.10).

RQ1 Step 4

The fourth step was to explore if the significant caseworker factors identified in step 3 remained significant after controlling for the predictors that were significant in step

2. This was done by adding the significant predictors into the model together. After entering all predictors into the model, nonsignificant predictors were removed from the final model.

Research Question 2

The second research question was: Do caseworker attitudes and beliefs toward child safety and family preservation predict removal decisions? This question was applied to the Attitudes Sample and had three primary analytic steps.

RQ2 Step 1

The first step was to calculate the ICC at the family and caseworker level (see Equations 3.6-3.8).

RQ2 Step 2

The second step was to calculate the bivariate relationships between attitudes toward child safety and family preservation, as measured by both surveys, and removal decisions. Because the caseworker variable gender was not included in the previous sample, the bivariate relationship between gender and the outcome was also calculated in this step. The bivariate relationships were assessed by adding each predictor into the model individually. Final models were run for each scale individually to assess each scale's influence without the other; the scales were significantly correlated, $r(189) = 0.36$, $p<.001$. One model was created for each survey:

a) Gender: was coded as 0 - 1 (0 = female, 1 = male), CGM, and entered into the model at level 2 (see Equation 3.10).

b) Against Removal scale: was CGM and entered into the model at level 2 (see Equation 3.10).

c) Dalgleish scale: was CGM and entered into the model at level 2 (see Equation 3.10).

RQ2 Step 3

The third step was to explore if attitudes toward child safety and family preservation predict removal decisions after controlling for the significant predictors identified in RQ1 steps 2 and 3. This was done by creating one model for gender and for each scale.

Research Question Three

The third research questions was: Does a worker's childhood history of adverse events predict removal decisions? This question was answered in three primary analytic steps and was applied to the ACE Sample.

RQ3 Step 1

The first step was to calculate the ICC at the family and caseworker level (see Equations 3.6-3.8).

RQ3 Step 2

The second step was to calculate the bivariate relationship between history of adverse experiences and removal. This was done by conducting a bivariate analysis of this survey and the outcome removal:

a) ACE survey: four dummy codes were created for the five ACE categories (0 ACEs, 1 ACE, 2 ACEs, 3 ACEs, 4 or more ACEs) with 0 ACEs coded as the reference group, each dummy code was grand mean centered, and entered at level 2 (see Equation 3.10).

RQ3 Step 3

The third step was to explore if a history of adverse experiences predicted removal decisions after controlling for the significant predictors identified in RQ1 steps 2 and 3.

RQ3 Step 4

Step 4 was to compare the proportion of CPS workers who had ACEs to ACEs rates in a U.S. sample that included ten states and Washington D.C. (Centers for Disease Control and Prevention, 2010) and the proportion of ACEs Utah (Utah Department of Health, 2011). This was done by conducting a chi-square test of independence:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad (3.11)$$

where

O_i is the observed frequencies and

E_i is the expected frequencies based on the population.

Post hoc tests were conducted as post hoc analysis of the omnibus chi-square test of independence to discover which proportions differed. This was done by conducting two-proportion *z*-tests:

$$z = \left(\frac{p_1 - p_2}{sqrt\left\{p\ (1-p)\left[\frac{1}{n_1} + \frac{1}{n_2}\right]\right\}} \right) \tag{3.12}$$

where

p_1 is the sample proportion from population 1,

p_2 is the sample proportion from population 1,

n_1 is the size of sample 1,

n_2 is the size of sample 2, and

$$p = \frac{(p_1 {*} n_1 + p_2 {*}\, n_2)}{(n_1 + n_2)}. \tag{3.13}$$

Research Question Four

The fourth research questions was: Do any of the survey scales, two measuring self-reported attitudes and beliefs towards child safety and family preservation and one measuring childhood history of adverse events, have predictive ability beyond the others? This question was applied to the Combined Sample.

RQ4 Step 1

The first step was to calculate the ICC at the family and caseworker level (see Equations 3.6-3.8).

RQ4 Step 2

The second step was to explore if either the attitudes scales or the ACE survey predicted removal beyond the others. This was completed by entering the significant predictors identified in RQ1, the two attitudes and belief scales, and ACE surveys into one model together.

CHAPTER 4

RESULTS

Descriptive Statistics

The CPS Sample was the largest sample that contained all the supported child case CPS investigations that took place between October 1, 2008 and July 31, 2016. The Attitudes, ACE, and Combined Samples included caseworkers who responded to the surveys. Participants in the Attitudes, ACE, and Combined Samples were compared to the CPS Sample to see if the individuals who responded to the survey were representative of the population of CPS workers. Table 4.1 shows the demographics of the caseworkers in each of the four samples. There was no difference in the composition of the CPS, Attitudes, ACE, or Combined Samples regarding race and ethnicity, χ^2 (18) = 4.54, p >.99. Accordingly, the caseworkers in the survey samples appear to be representative of the population of caseworkers who were CPS caseworkers between October 1, 2008 and July 31, 2016 with regard to the racial and ethnic composition of the workforce. The samples were not compared by gender because gender was not included as a variable in the CPS Sample.

Table 4.1 also shows the average years of experience with DCFS of the caseworkers by sample. Years of experience with DCFS at level 2, the caseworker level of the model, was skewed in each of these samples. Though the mean for each sample was just over 5 years, the median for each sample was lower (CPS Sample, median = 2.88; Attitudes Sample, median = 2.63; ACE Sample, median = 2.59; ACE Sample, median = 2.53). A Kruskal-Wallis test showed there was no difference between the three samples in the years of experience with DCFS, $H(3) = .12$, $p = .99$. Therefore, the caseworkers in the three survey samples appear to be representative of the population of caseworkers during this time period regarding years of experience with DCFS.

Table 4.1 also reports the scores on each of the surveys by sample. The Attitudes and Combined Samples included participants who completed the Dalgleish and Against Removal scales. The Combined Sample includes those participants who completed both the two attitudes scales, as well as the ACE survey. The average score for participants in the Attitudes Sample and Combined Sample on the Dalgleish scale were .37 ($SD = 1.72$) and .30 ($SD = 1.63$), respectively. Scores on the Dalgleish range from -5 to +5; a negative score represents attitudes and beliefs favorable toward family preservation, a positive score represents attitudes and beliefs favorable toward child safety, and a score of 0 represents a theoretical neutral attitude.

Table 4.2 displays the total number of child case at level 1 and the proportion of those child cases removed in each sample. There were differences between the three survey samples when compared to the CPS Sample in proportion of child cases removed, χ^2 (3) = 89.39, p <.001. *Z*-tests of proportions were conducted to find the differences between the samples (see Table 4.2). These tests revealed that compared, to the CPS Sample (12.16%), the Attitudes (13.39%), the ACE (12.64%), and the Combined (12.77%) samples had higher percentages of children removed from their homes. It appears then, that compared to the population of caseworkers, the survey samples were composed of caseworkers who remove a larger proportion of children.

The average score for participants in the Attitudes Sample and Combined Sample on the Against Removal scale were 2.64 (*SD* = .69) and 2.61 (*SD* = .73), respectively. Scores on the Against Removal scale range from 1 to 7. A lower score represents attitudes favorable toward family preservation, a higher score represents attitudes favorable toward child safety, and a score of 3.5 represents a theoretical neutral attitude. This means caseworkers in these samples are slightly on the family preservation side of this scale.

The ACE and Combined Samples included participants who completed the ACE scales. The Combined Sample includes those participants who completed both attitudes scales, as well as the ACE survey. In the ACE Sample, 26% of the caseworkers had no ACEs, 10% had one, 23% had two, 13% had three, and 27% had four or more. The Combined Sample was similar, 25% of the caseworkers has no ACEs, 10% had one, 24% had two, 13% had three, and 28% had four or more.

Research Question 1

The first research question was: Do caseworker factors predict removal decisions?

RQ1 Step 1

The first step was to calculate the variance at the family and caseworker levels. These ICCs were calculated using equations 3.6 – 3.8. The variances for families and caseworkers were 189.35 (*SD* = 13.76) and 0.86 (*SD* = 0.93), respectively. The ICC was 0.9786 for the random effect family and 0.0044 for the random effect for caseworker.

This means that, 97.86% of the variance lies between families and 0.44% lies within workers. The ICC for child cases that share the same family and caseworker was 0.9830. This means that 98.30% of the variance lies between child cases that share the same family and caseworker.

There does appear to be some variance between caseworkers. In a model with only a random effect for caseworkers, the ICC was .1589, meaning 15.89% of the variance is between caseworkers ($\sigma^2 = 0.6215$, SD = .79). However, with such low variance between caseworkers in the model with both random effects, the random effect for caseworker was not needed (Heck, Thomas, & Tabata, 2013) and was removed from the model. Also, because the Hessian matrix cannot be inverted, random effects near 0 can create model convergence problems (Gill & King, 2004).

Without the random effect for caseworker the model became a two-level model, where child cases were nested within families. In this model, the variance at the level of the family was 148.7 (*SD* = 12.19). The ICC at the family level was 0.9784, accordingly, 97.84% of the variance was between families and approximately 2.26% of the variance was within families.

RQ1 Step 2

The second step was to calculate the bivariate relationships between the region where the case was investigated and the case characteristics: child age, gender, race, ethnicity, and number of previous supported investigations with removal decisions. A separate model was run for each of the predictors to assess the relationship between each predictor and removal decisions without the impact of other predictors.

Each of these predictors were entered at level 1 of the models. These predictors were only of interest in the current study to control for their variance in the final model; therefore, the significance of the predictors was only highlighted here because these variables will be included in the later models. As discussed above, the coefficients are not interpretable and should not be interpreted.

Table 4.3 presents the odds ratios (*OR*) of the predictors from each model. Each of the comparisons for region was significant: Salt Lake Valley versus Eastern (*OR* = 1.67, $p < .001$), Salt Lake Valley versus Western (*OR* = 1.34, $p < .01$), Salt Lake Valley versus Eastern (*OR* = 1.68, $p < .001$), and Salt Lake Valley versus Southwest (*OR* = 1.41, $p < .05$). Number of previous supported investigations (*OR* = 1.72, $p < .001$) and the child's age (*OR* = .95, $p < .001$) significantly predicted removals. Two of the comparisons for child race and ethnicity were significant: Caucasian versus African American (*OR* = 1.75, $p < .01$) and Caucasian versus two or more race and ethnicities (*OR* = 1.86, $p < .001$). The gender of the child was not a significant predictor (odds ratio; *OR* = 1.09, $p = .055$). The significant predictors identified here were included in the later models to control for their variance when examining level 2 variables of interest.

RQ1 Step 3

The third step was to calculate the bivariate relationships between the caseworker minority status, correspondence between the caseworker's and child's race and ethnicity, and the caseworker's years of experience with DCFS. Table 4.3 also presents the odds ratios for each of these fixed effects from each model.

Caseworker minority status (*OR* = 1.07, $p = .42$) and race and ethnicity correspondence (*OR* = 1.08, $p = .21$) were not significant. This means there were no differences in removal decisions between caseworkers of minority and nonminority status. Also, there were no differences in removal decisions when the child was or was not of the same racial or ethnic group as the caseworkers.

There were, however, differences between caseworkers by years of experience with DCFS at both levels 1 and 2 of the model. As caseworkers increased in years of experience with DCFS, they were more likely to remove children from their homes (*OR* = 2.27, $p < .001$). This means as caseworkers increased one *SD* (*SD* = 4.98) of experience above their own average experience, they were 2.27 times more likely to remove children from their homes. The between-caseworker variance at level 2 was also significant (*OR* = 0.39, $p < .001$). The means that caseworkers with one *SD* (*SD* = 4.98) of experience below the average years of experience (*M* = 6.02), caseworkers were 2.56 times more likely to remove children from their homes. These are the coefficients with no control variables in the model and should be interpreted with caution.

RQ1 Step 4

The fourth step was to explore if the significant caseworker factors identified in step 3 remain significant after controlling for the significant level 1 predictors identified in step 2. This was done by entering all predictors into one model together. Predictors included region, child age, child ethnicity, number of previous supported investigations and caseworker years of experience with DCFS. Results are displayed in Table 4.4. Years of experience with DCFS was a significant predictor of removal, both within and between caseworkers.

As caseworkers increase in years of experience with DCFS, they are more likely to remove children from their homes ($OR = 2.10$, $p < .001$). This means that, after controlling for all other variables in the model, as caseworkers increase one *SD* ($SD =$ 4.98) of experience above their average experience, they are 2.10 times more likely to remove children from their homes. The between caseworker variance was at level 2 was also significant ($OR = 0.43$, $p < .001$). This means that, after controlling for all other variables in the model, caseworkers with one *SD* ($SD = 4.98$) of experience below the average years of experience ($M = 6.02$), caseworkers are 2.33 times more likely to remove children from their homes.

Research Question 2

The second research question was: Do caseworker attitudes and beliefs toward child safety and family preservation predict removal decisions? This question was applied to the Attitudes Sample and had three primary analytic steps.

RQ2 Step 1

The first step was to calculate the variance at the family and caseworker levels. The variances for families and caseworkers were 342.47 ($SD = 18.51$) and 1.09 ($SD =$ 1.05), respectively. The ICC was 0.9873 for the random effect family and 0.0031 for the random effect for caseworker. This means that, 98.73% of the variance was between families and 0.31% lies between workers. The ICC for child cases that share the same family and caseworker was 0.9905. This means that 99.05% of the variance was between child cases that share the same family and caseworker.

As with the above model, there was variance between caseworkers. In a model with only a random effect for caseworkers, the ICC was 0.1655, meaning 16.55% of the variance is between caseworkers (σ^2 =0.6425, SD = 0.80). However, with such low variance between caseworkers in the model with both random effects, the random effect for caseworker was not needed (Heck et al., 2013) and was removed from the model. Therefore, an unconditional model was run, where child cases were nested within families. The variance at the family level was 263.8 (SD = 16.24). The ICC at the family level was .9877, accordingly, 98.77% of the variance was between families and 1.23% of the variance was within families.

RQ2 Step 2

The second step was to calculate the bivariate relationships between attitudes toward child safety and family preservation, as measured by both surveys, and removal decisions. Also, because the caseworker variable gender was not included in the previous sample, the bivariate relationship between gender and the outcome was calculated in this step. The bivariate relationships were assessed by adding each predictor into the model individually.

Results for each of the bivariate analyses are displayed in Table 4.5. Each of these caseworker level predictors was significant. The gender of caseworker significantly predicted removal (OR = 0.79, p = .05). This means female caseworkers are 1.27 times more likely to remove a child than male caseworkers.

The Dalgleish scale significantly predicted removal (OR = 1.10, p < .01). This means that for every one point higher on the Dalgleish scale a worker is above the mean

($M = 0.42$), they are 1.10 times more likely to remove a child. Similarly, the Against Removal scale significantly predicted removals ($OR = 1.20$, $p < .05$). This means that for every one point higher on the Dalgleish scale a worker is above the mean ($M = 2.56$), they are 1.20 times more likely to remove a child. As with step 3 above, these coefficients should be interpreted with caution because no control variables were included in this model.

RQ2 Step 3

The third step was to explore if attitudes toward child safety and family preservation predict removal decisions after controlling for the predictors that were found to be significant in RQ1 steps 2 and 3 and caseworker gender in RQ2 step 2.

Results from the model with the Dalgleish scale are displayed in Table 4.6. As discussed above, the case level control variables will not be interpreted. Regarding the caseworker variables, in this model, the caseworker's gender was no longer significant ($OR = 0.80$, $p = .08$). The Dalgleish scale was also not significant ($OR = 1.05$, $p = .10$). Gender and Dalgleish scale were significantly correlated, $r_s(31,743)= -0.29$, $p < .001$).

Years of experience with DCFS remained significant after controlling for other variables in the model. As caseworkers increase in years of experience with DCFS, they are more likely to remove children from their homes ($OR = 2.45$, $p < .001$). This means that, after controlling for all other variables in the model, as caseworkers increase one *SD* ($SD = 4.96$) of experience above their average experience, they are 2.45 times more likely to remove children from their homes. The between caseworker variance was at level 2 was also significant ($OR = 0.32$, $p < .001$). This means that, after controlling for all other variables in the model, caseworkers with one *SD* (*SD* = 4.96) of experience below the average years of experience (*M* = 6.00), caseworkers were 3.13 times more likely to remove children from their homes.

The same model was run but the Dalgleish scale was replaced with the Against Removal scale. Table 4.7 displays the results this model. In this model, the Against Removal scale was not a significant predictor of removal (*OR* = 1.07, $p = .38$). Years of experience between caseworkers and the Against Removal scale were significantly correlated, $r(31{,}743) = -0.17$, $p < .001$).

The caseworker's gender was significant (*OR* = 0.77, $p < .05$). This means that, after controlling for the other variables in the model, female caseworkers were 1.30 times more likely to remove than male caseworkers. Years of experience with DCFS was significant at both levels of the model. As caseworkers increased in years of experience with DCFS, they were more likely to remove children from their homes (*OR* = 2.45, $p < .001$). This means that, after controlling for all other variables in the model, as caseworkers increased one *SD* (*SD* = 4.96) in experience above their own average experience, they were 2.45 times more likely to remove children from their homes. The between caseworker variance at level 2 was also significant (*OR* = 0.30, $p < .001$). This means that, after controlling for all other variables in the model, caseworkers with one *SD* (*SD* = 4.96) of experience below the average years of experience (*M* = 6.00) were 3.33 times more likely to remove children from their homes.

Research Question 3

The third research questions was: Does a worker's childhood history of adverse events predict removal decisions? This question was answered in three primary analytic steps and was applied to the ACE Sample.

RQ3 Step 1

The first step was to calculate the variance at the family and caseworker levels. The variance for families and caseworkers were 412.02 (*SD* = 20.30) and 1.11 (*SD* = 1.054), respectively. The ICC was .9894 for the random effect family and .0003 for the random effect for caseworker. This means that, 98.94% of the variance lies between families and 0.02% lies between workers. The ICC for child cases that share the same family and caseworker was .9921. This means that 99.21% of the variance lies between child cases that share the same family and caseworker.

In a model with only a random effect for caseworkers, the ICC was 0.1739, meaning 17.39% of the variance is between caseworkers (σ^2 =0.6926, *SD* = 0.8322). However, as with the above models, the random effect for caseworker was not needed due to the small amount of variance in the model with both random effects (Heck et al., 2013). Therefore, an unconditional model was run, where child cases were nested within families. The variance at the family level was 334.5 (*SD* = 18.29). The ICC at the family level was .9903, thus, 99.03% of the variance was between families less than 1% of the variance was within families.

RQ3 Step 2

The second step was to calculate the bivariate relationship between history of adverse childhood experiences and removal. This was done by conducting a bivariate analysis of this survey and the outcome removal. Table 4.8 displays the results of this model. Only one of the comparisons for the ACE variables was significant. Compared to caseworkers with no ACEs caseworkers with three ACEs were 1.54 times more likely to remove children from their homes (*OR* = 1.54, $p < .05$). Compared to caseworkers with no ACEs, there was no difference in removals for caseworkers who had one (*OR* = 1.48, $p = .10$), two (*OR* = 0.82, $p < .30$), or four or more (*OR* = 1.02, $p = .93$) ACEs.

RQ3 Step 3

The third step was to explore if a history of adverse experiences predicts removal decisions after controlling for the predictors that were found to be significant in RQ1 steps 2 and 3 and caseworker gender in RQ2. Results for this model are displayed in Table 4.9.

The gender of the caseworker was significant (*OR* = .59, $p = .01$). This means that, after controlling for all other predictors in the model, female caseworkers are 1.69 times more likely to remove a child than male caseworkers.

The number of ACEs was a significant predictor for two of the four comparisons in the model. Compared to caseworkers with no history of ACEs, caseworkers with two ACEs were less likely to remove children from their homes (*OR* = 0.61, $p < .05$), as were caseworkers with four or more ACES (*OR* = 0.65, $p = .05$). This means that, after controlling for all other predictors in the model, caseworkers with no ACEs are 1.64

times more likely to remove children than caseworkers with two ACEs. Similarly, caseworkers with no ACEs were 1.54 times more likely to remove a child than caseworkers who had four or more ACEs. There was no difference for caseworkers with one ACE (*OR* = 1.20, $p = .48$) or three ACEs (*OR* = 0.92, $p = .72$).

Experience was also a significant predictor of removal. As caseworkers increased in years of experience with DCFS, they were more likely to remove children from their homes (*OR* = 2.05, $p < .01$). This means that, after controlling for all other variables in the model, as caseworkers increased one *SD* (*SD* = 4.86) of experience above their average experience, they were 2.05 times more likely to remove a child from their home. The between caseworker variance was at level 2 was also significant (*OR* = 0.35, $p < .001$). This means that, after controlling for all other variables in the model, caseworkers with one *SD* (*SD* = 4.86) of experience below the average years of experience (*M* = 5.73), caseworkers were 2.86 times more likely to remove children from their homes.

RQ3 Step 4

Step 4 was to compare the proportion of CPS workers who had ACEs to ACEs rates in a U.S. sample that included 10 states and Washington D.C. (Centers for Disease Control and Prevention, 2010) and the proportion of ACEs Utah (Utah Department of Health, 2011). This was done by conducting a chi-square test of independence and post hoc *z*-tests of independent proportions (equations 3.11 to 3.13). The results of the chi-square tests of independence showed there were significant differences between the sample of CPS caseworkers and U.S. sample, χ^2 (4) = 49.82, $p <.001$, and the sample of CPS caseworkers and Utah sample, χ^2 (4) = 51.25, $p <.001$.

As can be seen in Table 4.10 and 4.11, there were significant differences between the sample of CPS caseworkers who had ACE compared both the U.S. and Utah samples. The CPS caseworkers have significantly more ACEs than the U.S. sample and Utah sample.

Research Question 4

The fourth research questions was: Do any of the surveys, two measuring self-reported attitudes and beliefs toward child safety and family preservation and one measuring childhood history of adverse events, have predictive ability beyond the others? This question was applied to the Combined Sample.

RQ4 Step 1

The first step was to calculate the variance at the family- and caseworker-levels using equations 3.6 – 3.8. The variance for families and caseworkers were 408.37 (*SD* = 20.21) and 1.03 (*SD* = 1.01), respectively. The ICC was 0.9895 for the random effect family and 0.0025 for the random effect for caseworker. This means that, 98.95% of the variance lies between families and 0.25% lies between workers. The ICC for child cases that share the same family and caseworker was 0.9920. This means that 99.20% of the variance lies between child cases that share the same family and caseworker.

In a model with only a random effect for caseworker, 17.54% of the variance is between caseworkers (σ^2 =0.6997, *SD* = 0.8365). However, due to the small amount of variance in the model with both random effects, the random effect for caseworker was removed (Heck et al., 2013). An unconditional model was run with child cases nested within families. The variance at the family level was 337.7 (*SD* = 18.36). The ICC at the family level was .9903. Thus, 99.03% of the variance is between families and less than 1.00% of the variance is within families.

RQ4 Step 2

The second step was to explore if either attitudes scales, Dalgleish or Against Removal, or the ACE survey predicted removal beyond the others. To answer this question, the significant predictors identified in RQ1 and RQ2, the two attitudes scales, and the ACE survey were entered into a model together. Results are displayed in Table 4.12.

For the caseworker predictors, gender of the caseworker was not significant (*OR* = 0.67, p = .06). When compared to not having a history of ACEs, having one (*OR* = 1.42, p = .20), two (*OR* = 0.71, p = .13), three (*OR* = 1.14, p = .58), or four or more (*OR* = 0.69, p < .09) ACEs did not predict removals. The Against Removal scale (*OR* = 1.10, p = .36) and the Dalgleish scale were not predictive of removal (*OR* = 1.09, p < .08).

Caseworker years of experience with DCFS remained significant in this model. As caseworkers increased in years of experience with DCFS, they were more likely to remove children from their homes (*OR* = 2.04, p < .01). This means that, after controlling for all other variables in the model, as caseworkers increased one *SD* (*SD* = 4.85) of experience above their average experience, they were 2.04 times more likely to remove children from their homes. The between caseworker variance was at level 2 was also significant (*OR* = 0.36, p < .001). This means that, after controlling for all other variables in the model, caseworkers with one *SD* (*SD* = 4.85) of experience below the average years of experience (*M* = 5.77) were 2.78 times more likely to remove children from their homes.

Table 4.1
Caseworkers Demographics

	CPS Sample (n = 516)	Attitudes Sample (n = 191)	ACE Sample (n = 143)	Combined Sample (n = 134)
	%	% or M	% or M	% or M
Gender				
Female		69	66	66
Male		31	34	34
Race and ethnicity[a]				
African American[b]	<1	0	0	0
American Indian or Alaskan[b]	1	1	1	1
Asian[b]	1	2	1	2
Caucasian[b]	91	90	90	90
Latino or Hispanic	6	7	6	6
Pacific Islander[b]	<1	1	1	2
Two or more[b]	<1	1		1
Years of experience				
With DCFS	5.02	5.02	5.17	5.03
Attitude Surveys				
Dalgleish[c]		0.37 (1.72)		0.30 (1.63)
Against Removal[c]		2.64 (0.69)		2.61 (0.73)
ACE Survey				
0 ACES			26	25
1 ACE			10	10
2 ACES			23	24
3 ACES			13	13
4 or more ACES			27	28

Note. All are a. Z-test for proportions compared the latter three samples with the CPS sample, all were nonsignificant. b. Non-Hispanic. c. Standard deviation reported in parentheses.

Table 4.2
Percent of Child Cases Removed

	Child cases removed		
	N[a]	%	*z*[b]
CPS Sample	77,173	12.17	
Attitudes Sample	31,745	13.40	-5.55[c***]
ACE Sample	21,239	13.95	-6.91[c***]
Combined Sample	20,404	14.09	-7.35[c***]

Note. a. Child cases at level 1. b. *z*-test of proportions
c. Compared to CPS Sample. *** = p <.001.

Table 4.3
CPS Sample Bivariate Analyses

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Region[a]		
Northern	1.67***	1.37, 2.03
Western	1.34**	1.08, 1.66
Eastern	1.68***	1.26, 2.23
Southwest	1.41*	1.08, 1.86
Previous supported investigation	1.72***	1.60, 1.84
Child Age	0.95***	0.94, 0.96
Child Ethnicity[b]		
African American[c]	1.75**	1.22, 2.51
American Indian or Alaskan[c]	0.65	0.41, 1.03
Asian[c]	1.31	0.65, 2.65
Latino or Hispanic	0.95	0.81, 1.11
Pacific Islander[c]	0.68	0.36, 1.28
Two or more[c]	1.86***	1.31, 2.63
Child Gender	1.09	1.00, 1.20
Caseworker minority status	1.07	0.90, 1.28
Ethnicity correspondence	1.08	0.96, 1.23
Within caseworker years of experience with DCFS[d]	2.27***	1.89, 2.72
Between caseworker years of experience with DCFS[d]	0.39***	0.32, 0.47

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic, d. *z*-scored.
* = p <.05, ** = p <.01, *** = p <.001

Table 4.4
CPS Sample Full Model

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Intercept	0.00***	0.00, 0.00
Region[a]		
Northern	1.77***	1.44, 2.17
Western	1.50***	1.20, 1.88
Eastern	1.69***	1.25, 2.29
Southwest	1.47**	1.10, 1.95
Previous supported investigation	2.53***	2.32, 2.75
Child Age	0.89***	0.88, 0.90
Child Ethnicity[b]		
African American[c]	1.89***	1.29, 2.77
American Indian or Alaskan[c]	0.63	0.38, 1.05
Asian[c]	1.77	0.74, 4.22
Latino or Hispanic	0.97	0.82, 1.14
Pacific Islander[c]	0.78	0.39, 1.59
Two or more[c]	1.86***	1.29, 2.69
Within caseworker years of experience with DCFS[d]	2.10***	1.74, 2.53
Between caseworker years of experience with DCFS[d]	0.43***	0.35, 0.52

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic d. *z*-scored.
** = p <.01, *** = p <.001.

Table 4.5
Attitudes Sample Bivariate Analyses

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Caseworker gender	0.79*	0.63, 0.99
Dalgleish scale	1.10**	1.04, 1.16
Against Removal scale	1.20*	1.04, 1.39

* = p <.05, ** = p <.01

Table 4.6
Attitudes Sample Dalgleish Full Model

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Intercept	0.00***	0.00, 0.00
Region[a]		
Northern	2.30***	1.56, 3.39
Western	1.75*	1.09, 2.81
Eastern	1.90*	1.13, 3.20
Southwest	1.55	0.91, 2.61
Previous supported investigation	2.34***	1.99, 2.74
Child Age	0.88***	0.86, 0.90
Child Ethnicity[b]		
African American[c]	2.22*	1.15, 4.31
American Indian or Alaskan[c]	0.53	0.21, 1.33
Asian[c]	1.52	0.30, 7.76
Latino or Hispanic	1.04	0.77, 1.41
Pacific Islander[c]	1.67	0.54, 5.14
Two or more[c]	1.28	0.65, 2.53
Caseworker gender	0.80	0.62, 1.03
Within caseworker years of experience with DCFS[d]	2.45***	1.75, 3.43
Between caseworker years of experience with DCFS[d]	0.32***	0.23, 0.45
Dalgleish scale	1.05	0.99, 1.12

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic, d. *z*-scored.
* = p <.05, ** = p <.01, *** = p <.001.

Table 4.7
Attitudes Sample Against Removal Full Model

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Intercept	0.00***	0.00, 0.00
Region[a]		
Northern	2.23***	1.58, 3.43
Western	1.71*	1.07, 2.75
Eastern	1.84*	1.07, 2.75
Southwest	1.53	0.90, 2.58
Previous supported investigation	2.34***	2.00, 2.75
Child Age	0.88***	0.86, 0.90
Child Ethnicity[b]		
African American[c]	2.20*	1.13, 4.28
American Indian or Alaskan[c]	0.52	0.21, 1.31
Asian[c]	1.51	0.30, 7.65
Latino or Hispanic	1.05	0.77, 1.42
Pacific Islander[c]	1.67	0.54, 5.13
Two or more[c]	1.28	0.65, 2.54
Caseworker gender	0.77*	0.60, 0.98
Within caseworker years of experience with DCFS[d]	2.45***	1.75, 3.43
Between caseworker years of experience with DCFS[d]	0.30***	0.21, 0.43
Against Removal scale	1.07	0.92, 1.26

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic, d. *z*-scored.
* = p <.05, ** = p <.01, *** = p <.001.

Table 4.8
ACE Sample Bivariate Analyses

	Fixed effect parameter estimates	
	Odds ratio	95% CI
ACEs[a]		
1 ACE	1.48	0.92, 2.38
2 ACEs	0.82	0.56, 1.20
3 ACEs	1.54*	1.01, 2.33
4 ACEs	1.02	0.71, 1.46

a. Reference group: 0 ACEs
* = p <.05

Table 4.9
ACE Sample Full Model

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Intercept	0.00***	0.00, 0.00
Region[a]		
Northern	1.95*	1.13, 3.35
Western	1.45	0.80, 2.63
Eastern	1.53	0.82, 2.87
Southwest	1.95	0.95, 4.01
Previous supported investigation	2.36***	1.91, 2.90
Child Age	0.88***	0.85, 0.91
Child Ethnicity[b]		
African American[c]	3.08*	1.29, 7.38
American Indian or Alaskan[c]	0.76	0.26, 2.16
Asian[c]	0.96	0.09, 10.5
Latino or Hispanic	0.99	0.66, 1.47
Pacific Islander[c]	2.16	0.51, 9.16
Two or more[c]	1.15	0.44, 2.96
Caseworker gender	0.59**	0.39, 0.88
Within caseworker years of experience with DCFS[d]	2.05**	1.29, 3.24
Between caseworker years of experience with DCFS[d]	0.34***	0.21, 0.56
ACEs[e]		
1 ACE	1.20	0.72, 2.02
2 ACEs	0.61*	0.40, 0.93
3 ACEs	0.92	0.58, 1.46
4 ACEs	0.65*	0.43, 0.97

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic, d. *z*-scored, e. Reference group: 0 ACEs.
* = p <.05, ** = p <.01, *** = p <.001.

Table 4.10
Percentage of Individuals With ACEs Attitudes Sample vs. U.S. Sample

	ACE Sample (n = 191)	U.S. Sample (n = 53,748)	Z
	%	%	%
ACE Survey			
0 ACES	25.9	40.7	3.61^{***}
1 ACE	10.5	23.6	3.69^{***}
2 ACES	23.1	13.3	-3.43^{***}
3 ACES	13.3	8.1	-2.26^{*}
4 or more ACES	27.3	14.3	-4.42^{***}

Note. *Z*-test for proportions compared ACE Sample with the U.S. Sample.
* = p <.05, ** = p <.01, *** = p <.001.

Table 4.11
Percentage of Individuals With ACEs Attitudes Sample vs. Utah Sample

	ACE Sample (n = 191)	Utah Sample (n = 2,307)	Z
	%	%	%
ACE Survey			
0 ACES	25.9	41.1	4.25***
1 ACE	10.5	20.7	3.16***
2 ACES	23.1	14.8	-3.21***
3 ACES	13.3	7.9	-2.35*
4 or more ACES	27.3	15.5	-4.71***

Note. Z-test for proportions compared ACE Sample with the Utah Sample.
* = p <.05, ** = p <.01, *** = p <.001.

Table 4.12
Combined Sample Full Model

	Fixed effect parameter estimates	
	Odds ratio	95% CI
Intercept	0.00***	0.00, 0.00
Region[a]		
Northern	1.70	0.99, 2.93
Western	1.48	0.82, 2.69
Eastern	1.30	0.70, 2.44
Southwest	1.65	0.80, 3.39
Previous supported investigation	2.41***	1.95, 2.96
Child Age	0.88***	0.85, 0.91
Child Ethnicity[b]		
African American[c]	2.97*	1.24, 7.12
American Indian or Alaskan[c]	0.75	0.26, 2.16
Asian[c]	0.93	0.09, 10.2
Latino or Hispanic	0.98	0.66, 1.46
Pacific Islander[c]	2.19	0.52, 9.28
Two or more[c]	0.94	0.36, 2.44
Caseworker gender	0.67	0.39, 1.15
Within caseworker years of experience with DCFS[d]	2.04**	1.37, 3.04
Between caseworker years of experience with DCFS[d]	0.36***	0.26, 0.51
Dalgleish scale	1.09	0.73, 1.63
Against Removal Scale	1.10	0.70, 1.75
ACEs[e]		
1 ACE	1.42	0.90, 2.24
2 ACEs	0.71	0.44, 1.16
3 ACEs	1.14	0.68, 1.92
4 ACEs	0.69	0.45, 1.05

a. Reference group: Salt Lake Valley, b. Reference group: non-Hispanic Caucasian, c. non-Hispanic, d. *z*-scored, e. Reference group: 0 ACEs.
* = p <.05, ** = p <.01, *** = p <.001.

CHAPTER 5

DISCUSSION

There are considerable inconsistencies in the decisions made by child welfare caseworkers regarding removing children from their homes (Graham et al., 2015). This variation in decisions goes beyond variance that can be explained by factors related to the case, such as the level of risk of future abuse (Dettlaff et al., 2015; Fluke et al., 2014; Gold et al., 2001; Rossi et al., 1999). Additionally, inconsistencies in decision making remain despite interventions by child welfare agencies, such as the introduction of safety and risk assessment tools aimed at decreasing subjectivity in the assessment process.

Understanding which factors influence caseworkers in the removal decisions they make is of utmost importance, as these decisions profoundly impact the lives of children and families. Efforts are being made to minimize unwanted variance by first organizing research around common hypotheses and constructs. For example, the DME is a framework for understanding decisions made in child welfare (Baumann et al., 2011, 2014; Fluke et al., 2014). The creators of the DME postulate that there are many factors that influence removal decisions. They organize these factors into four categories: organizational factors, external factors, case factors, and decision-maker (caseworker) factors.

The purpose of this study was to explore whether caseworker characteristics influence the removal decisions they make during CPS investigations. These characteristics were explored using child welfare administrative data and self-report surveys completed by CPS caseworkers in Utah. Attitudes toward child safety, family preservation, and history of adverse childhood experiences were assessed using the self-report surveys completed by caseworkers.

Influence of Caseworker Characteristics

Caseworker characteristics I investigated in this study included the caseworker's minority status, correspondence between the caseworker's and children's race and ethnicity, the caseworker's gender, the years of experience the caseworker had with DCFS, the caseworker's attitudes toward child safety and family preservation, and the caseworker's childhood history of adverse experiences. Child-case factors, including the age of the child, race and ethnicity of the child, and number of previous supported investigations in which the child was involved, and the region in which the case was investigated, were included in the full models as control variables. The findings in this section are organized around my four research questions.

The first research question was: Do caseworker characteristics predict removal decisions? The caseworker characteristics I explored in this research question included the caseworker's minority status, correspondence between the caseworker's and children's race and ethnicity, the caseworker's gender, the years of experience the caseworker had with DCFS. In this section, findings regarding each of the characteristics investigated are discussed across samples and analyses.

Minority Status and Ethnicity Correspondence

The minority status of the caseworker and the correspondence of race and ethnicity between the caseworker and child did not predict removal decisions in the bivariate analysis. This means that Caucasian caseworkers and minority caseworkers did not differ in removal rates. Additionally, caseworkers appeared to be consistent in removal decisions regardless of whether their race and ethnicity was the same as or different from that of the child.

It is important to consider, though, that the majority of the caseworkers (91%) in this study were Caucasian. Additionally, due to the small number of minority caseworkers, all caseworkers of minority racial and ethnic backgrounds were grouped together and differences between the groups were not considered. More variation in removal decisions may be seen in more diverse workforces. It is possible that caseworkers of different minority racial and ethnic backgrounds make different removal decisions. For example, Font, Berger, and Slack (2012) found that, compared to Caucasian caseworkers, African American caseworkers rated Caucasian children as lower risk for future maltreatment. Additionally, the African American caseworkers were more likely to substantiate allegations of maltreatment for all families. The researchers posited that African American caseworkers may have different perceptions of what constitutes abuse than Caucasian caseworkers. However, significant differences in risk assessments and rates of substantiation were also found between communities. Therefore, Font, Berger, and Slack concluded differences observed between African American and Caucasian caseworkers may be attributable to the differences in the communities served by those caseworkers, rather than differences between caseworkers. They highlighted that African American caseworkers tended to be assigned to cases with African American children and families in homogenous communities. Additionally, these communities are frequently disproportionately impacted by risk factors such as poverty and substance abuse.

Nevertheless, the findings in the present study, that there were no differences between caseworkers by race and ethnicity correspondence with the child, are consistent with other empirical findings in this area. For example, Graham et al. (2015), found no differences in placement decisions between caseworkers of different racial and ethnic groups. Similarly, Fluke et al. (2016) found there were no differences in attitudes toward child safety and family preservation by the caseworkers' race and ethnicity. Finally, Rolock and Testa (2005) found no differences in substantiation rates by the race of the caseworkers.

Years of Experience With DCFS

This section reviews findings across samples related to the years of experience of the caseworker. The discussion first briefly reviews the methods and summarizes the findings across samples.

For each of the samples and analyses, years of experience was partitioned into within-caseworker years of experience and between-caseworker years of experience. Years of experience included all experience an individual had with DCFS, not limited to time as a CPS caseworker. Within-caseworker years of experience with DCFS represented how removal decisions changed over time as caseworkers gained experience within the child welfare agency. Between-caseworker years of experience represented how removal rates differed for caseworkers by the number of years of experience. Accordingly, the latter variable allowed for comparison of removal rates between caseworkers who had different years of experience with DCFS.

Years of experience with DCFS both within and between caseworkers significantly predicted removal decisions in the bivariate analyses in the CPS Sample and after controlling for other variables in each of the subsequent models across samples. Across samples, the control variables included: the region in which the case was investigated, the number of previous investigations in which a child was involved, the age of the child, and the race and ethnicity of the child. Additionally, in the Attitudes Sample the Dalgleish scale and the Against Removal scale were included. In the ACE Sample, the ACE survey was included. Finally, the Combined Sample included each of these survey scales.

Years of Experience Within Caseworkers

Years of experience with DCFS within caseworkers was significant and positively related to removal decisions in each of the samples and analyses. This means that as caseworkers gained experience with DCFS, they were more likely to remove children from their homes. While it is known that service providers will drift away from fidelity from training overtime if adherence is not measured (Fixsen, Blase, Naoom, & Wallace, 2009), the finding that caseworkers would drift more toward child safety was unexpected. Studies have found either no relationship between attitudes toward child safety and family preservation (Arad-Davidzon & Benbenishty, 2008; Font & Maguire-Jack, 2015; Graham et al., 2015) or a positive relationship between years of experience and attitudes favorable toward family preservation (Brunnberg & Pećnik, 2007; Davidson-Arad et al., 2003; Fluke et al., 2016). Though these studies focused on vignettes and not real-world decisions, it was anticipated that decision-making behavior and experience would have a similar relationship.

Importantly, risk was controlled for by including the child's age and number of previous supported investigations in the model. Therefore, these results do not appear to be attributable to caseworkers being assigned more difficult cases over time. Nevertheless, this does not entirely eliminate risk as a confounding variable as other potentially important predictors of risk were not included, such as poverty, parental substance abuse, and the type of maltreatment that brought the child to the attention of the child welfare agency (White, Hindley, & Jones, 2015).

From an expected utility perspective, both the decision to leave children in their home and to remove children can be seen as having some utility. The decision to leave children in their home is valuable because children remain with their families while parents or guardians work toward improved parenting skills. On the other hand, value can be found in the decision to remove a child from their home because children are viewed as having a decreased likelihood in risk of maltreatment. However, based on increased removal rates over time, it appears caseworkers grew to value the benefits of removal and a higher guarantee of child safety over family preservation.

The finding that caseworkers are more likely to remove children as they gain experience demonstrates that caseworkers orient more to child safety in their removal decisions over time, though the cause of this drift is unknown. One potential explanation for this trend is that they may become more conservative with regard to child safety due to negative consequences of their removal decisions. That is, the act of leaving children in their homes and the children experiencing new incidents of serious maltreatment had a greater impact on caseworkers than the trauma families experienced when children were removed from their homes. This explanation is supported by the findings of researchers who have investigated the impact of serious negative child outcomes, such as child fatalities. In such cases it seems caseworkers become more anxious about child safety. For example, these studies suggest that caseworkers worry children on their caseload will suffer major maltreatment that will result in death (Douglas, 2012) and that caseworkers experience serious emotional distress following child fatalities (Douglas, 2013). It is noted, however, that this research focused primarily on caseworkers who carry the case on an ongoing basis, rather than CPS investigators.

This preference for child safety could also be due to the mechanism of outcome feedback available to caseworkers. New instances of maltreatment can be easily quantified and potentially accessed by caseworkers. This could be through official methods, such as annual reports, for example. Or, this could be through unofficial methods, such as the caseworkers' perception shaped by feedback to caseworkers through anecdotal means, such as seeing children and families return to the system for new allegations of maltreatment (Baumann et al., 2011, 2014; Fluke et al., 2014). However, the trauma or impact of removal on well-being is not measured by most child welfare agencies. Additionally, it is difficult to separate the impact of a removal from the impact of previous maltreatment. Thus, feedback on the impact of a removal is not as readily available to the caseworkers to impact future decision making.

While this study did not explore the use of heuristics, another possible explanation for the finding that caseworkers are more likely to remove children as they gain experience is that caseworkers developed personal heuristics that shift their decision-making tendencies. As an example, the availability heuristic may shape decisions made over time. According to this heuristic, individuals infer the likelihood of an outcome based on the ease with which examples of the outcome come to mind, or the availability of the outcome (Tversky & Kahneman, 1974). An outcome's availability is influenced by other factors, such as the emotional salience of an event. For example, a caseworker may have cases where they did not remove children from their homes and those children then experienced a serious new instance of maltreatment. Those cases may have more emotional salience and thus be more available to the caseworker than cases with more benign outcomes. Then when that caseworker investigates cases that are similar to those cases, the possible serious negative outcomes of that case could be more prominent in the caseworker's mind and in that case the caseworker may be apt to conclude that the serious negative outcome is the most probable. Thus, the availability heuristic could then subconsciously influence caseworkers to overestimate the risk of future maltreatment and to emphasize child safety in future decisions. If this finding is replicated in other studies, the causes of this trend should be explored. The impact of serious negative child outcomes and mechanisms of outcome feedback on decision are in need of further exploration. Additionally, the development of personal heuristics is also a potential explanation that is worthy of future research.

Years of Experience Between Caseworkers

Years of experience between caseworkers was also a significant predictor of removal, meaning there was a significant difference between caseworkers with different average years of experience working with DCFS. Here, however, the opposite relationship was observed with removal decisions. Caseworkers with more average years of experience with DCFS were less likely to remove children than caseworkers with less experience. This discrepancy in the relationships of the within- and between-caseworker years of experience variables is not intuitive; however, what these findings indicate is that, while all caseworkers were more likely to remove children as they gained experience, there was something different about caseworkers who stayed with the agency longer, making them overall less likely to remove a child.

Though this study found differences in removal rates between caseworkers with different years of experience, the cause for these differences is unknown. Based on the findings in this study, it appears there is something unique about caseworkers who remain in the child welfare field. This result could be due to cohort effects, such as age, life experience, or generational differences. Or this finding may be attributable to organizational differences, such as variance in training and supervision over time.

It is also possible that caseworkers who placed higher value, or utility, on child safety have left the agency due to conflicts between agency policies and their personal attitudes and belief systems, as the child welfare system in Utah has recently placed an increased emphasis on family preservation (Social Research Institute, 2016). Thus, it is possible that only caseworkers whose beliefs are commensurate with the focus on family preservation have remained. As a result, caseworkers with more years of experience had lower removal rates than caseworkers who had worked for the agency only briefly or who were only recently hired. As discussed above, these findings are commensurate with research that has found workers with more child welfare experience have attitudes more favorable toward family preservation and are less likely to recommend removal (Brunnberg & Pećnik, 2007; Davidson-Arad et al., 2003; Fluke et al., 2016).

While the present study cannot explain this finding, there are some potential areas worth exploring to further understand the influence of experience on decision making. Future research should explore what these characteristics are as they relate to removal decisions. As discussed above, these could be due to caseworker variables such as generation and age of the caseworker or organizational variables such as training and supervision. Synergy between the attitudes and beliefs of the caseworker and organizational goals and values warrant future exploration, as it is possible that caseworkers who do not align with the goals and values of the agency could be exiting the workforce at higher rates. Finally, to replicate the findings in this study, future research should partition the within and between caseworker variance when exploring caseworker decisions made over time.

Caseworker Gender

The caseworker's gender was not included as a predictor in the CPS Sample due to the high number caseworkers whose gender was missing in the human resources data. Gender was included as a predictor in each of the analyses conducted with the survey samples. The caseworker's gender was a significant predictor of removal in the bivariate analysis in the Attitudes Sample, the largest of the survey samples. Accordingly, it was included in each of the subsequent full models.

The gender of the caseworker was a significant predictor of removal in two of the four analyses. In the Attitudes Sample, after controlling for the region and the child-level control variables, the caseworkers' years of experience both within and between caseworkers, and the Against Removal scale, male caseworkers were less likely to remove children than female caseworkers. Additionally, after controlling for each of these variables but with the ACE survey instead of the Against Removal scale, the same results were found. This finding was somewhat unexpected because Fluke et al. (2016) found no differences between males and females on their orientation toward child safety or family preservation.

In the present study, on one of the scales for attitudes toward child safety and family preservation, the Dalgleish scale, there was a positive correlation between females and a child safety orientation. Thus, it is possible that females are generally more risk avoidant than males. This would mean that female caseworkers have a lower threshold for the risk of further maltreatment inherent in leaving children in their homes. Very few empirical studies have focused on risk-taking on behalf of others (Hibbing & Alford, 2005). With regard to risk-taking on behalf of others in medical settings, one study found females scored higher on an Anxiety Due to Uncertainty scale (Allison et al., 1998). The same study also found that individuals who scored high on this scale had higher Medicare HMO costs due to ordering more procedures. Thus, it appears that female physicians err on the side of safety—or ordering more procedures—when under conditions of uncertainty.

A study that investigated betting behavior found males made riskier bets overall both for themselves and others (Cvetkovich, 1972). However, studies in the field of economics have found discrepant results by gender in decisions made for others. Some studies have found no difference by gender (Charness & Jackson, 2009; Pahlke, Strasser, & Vieider, 2012) and one study found males made safer investment choices for others than females (Eriksen & Kvaloy, 2010).

The differences in removal rates by gender may also be due to differential attitudes between males and females on acceptable parenting practices and perception of behaviors as abusive. Though there is limited empirical evidence on this topic, research suggests males have a more favorable attitude toward harsh physical punishment than females (Flynn, 1998). For example, one study found males rated physical discipline as more acceptable than females (Budd et al., 2012). Similarly, researchers have found gender differences in whether individuals perceive caregivers' behaviors as abusive, where females were more likely to interpret an act as abusive and indicated they would report the incident to child welfare authorities (Al-Moosa, Al-Shaiji, Al-Fadhli, Al-Bayed, & Adib, 2003; Dukes & Kean, 1989; Hansen et al., 1997; Howe, Herzberger, & Tennen, 1988; Koski & Mangold, 1988). This is similar to research that found females were more likely to believe an allegation of maltreatment is true (Cromer & Freyd, 2007, 2009; Cunningham & Cromer, 2016; Jackson & Nuttall, 1994).

While this research may provide some insight into why these gender differences in removal patterns exist, there are limits to the support of these hypotheses as an explanation for differential removal decisions. Some studies have found no differences by gender on perceptions of behaviors as abusive and intentions to report to child welfare (Ashton, 1999, 2004). Additionally, the present study included only cases where the maltreatment allegation had been found to have merit. Thus, all instances of abuse are assumed to be true.

Nevertheless, in the present study, gender was not significant in two of the analyses. After controlling for the Dalgleish scale in the Attitudes Sample and the Dalgleish scale and the ACEs in the Combined Sample, gender was not a significant predictor of removal decisions. What these two analyses had in common was that the caseworkers' score on the Dalgleish scale was included as a predictor in both of the analyses. The Dalgleish scale and gender were significantly correlated and so it is possible these two predictors shared enough variance with the outcome that neither was predictive when modeled together.

Caseworker Attitudes and Beliefs Toward Child Safety and Family Preservation

The second research question was: Do caseworker attitudes and beliefs toward child safety and family preservation predict removal decisions? This research question included an exploration of the predictive ability of the Dalgleish scale and the Against Removal scale. Findings regarding each of these scales are discussed across samples and analyses.

Attitudes and beliefs toward child safety and family preservation did not predict removals above the other pertinent variables included in the models. Though both the Dalgleish and Against removal scales were significant predictors of removal in the bivariate models, they were not significant in the survey sample models after controlling for the child-case predictors, region in which the case was investigated, the gender of the caseworker, and the experience of the caseworker. These findings were somewhat surprising because the Against Removal scale has been found to be predictive of removal decisions in studies that have used vignettes to explore decision making behavior (Benbenishty et al., 2015; Davidson-Arad & Benbenishty, 2010, 2016). Nevertheless, the results in the present study are commensurate with findings by Graham et al. (2015) who found no direct relationship between attitudes and removal decisions using real-world decisions, though different measures were used in this study.

The null findings may be attributable to the relationship between attitudes and beliefs and other variables in the model. For example, attitudes and beliefs were related to both gender and experience. Thus, as discussed above, it is possible that attitudes and beliefs shared enough variance with the outcome that attitudes and beliefs were not predictive when modeled with gender and years of experience variables. Similarly, though not specifically explored in this study, it could be that attitudes and beliefs and the influence of those attitudes and beliefs on decisions varied across regions such that after controlling for region, they were no longer significant predictors of removal. For example, researchers have found differential removal rates between communities and areas (Dettlaff & Rycraft, 2008; Fluke et al., 2010; Font & Maguire-Jack, 2015).

Additionally, attitudes toward and beliefs about child safety and family preservation were applied to the caseworkers' histories of removal decisions. However, no longitudinal data on attitudes and beliefs were gathered. It is possible that attitudes and beliefs toward child safety and family preservation change over time (Fluke et al., 2016). If this is true, then it would not be expected that caseworkers' attitudes and beliefs would predict their history of removal decisions.

Similarly, it could be that attitudes and beliefs are more influential at different points in a caseworker's career or in different organizational structures. For example, attitudes could be more influential as caseworkers gain more experience. A finding such as this would fit with research that suggests drift from training and program design will happen overtime (Fixsen et al., 2009). Likewise, attitudes may be more influential during periods with different policy and practice standards, where the influence of attitudes and beliefs would be stronger where policy and practice guidelines are less structured. For example, Chabot et al. (2013) found variance in removal decisions was greater in areas where child welfare organizations were not centralized.

Attitudes and beliefs toward child safety and family preservation are a potential malleable factor that child welfare agencies could target in trainings in order reduce variance in decision making (Fluke et al., 2016). Thus, due to significant findings in the bivariate analyses in the present study and the mixed findings across studies, further investigation is needed. Research should focus on exploring how attitudes and beliefs relate to other personal characteristics and organizational factors, as well as how they change over time.

Adverse Childhood Experiences

The third research question was: Does a worker's childhood history of adverse events predict removal decisions? The ACE survey was used to measure these adverse events. Findings regarding the ACE survey are discussed across samples and analyses in this section.

In the ACE Sample, a model was run that included each of the control variables:

the region in which the case was investigated, the number of previous investigations in which the child was involved, the age of the child, the race and ethnicity of the child, the gender of the caseworker, and the years of experience of the caseworker. In this model, compared to caseworkers who had no ACEs, caseworkers with two and four ACEs were less likely to remove children from their homes. The comparisons for caseworkers with one and three ACEs were not significant. It is interesting that caseworkers with three ACEs appeared to be equally as likely to remove children from their homes. This result may, however, be due to the small number of caseworkers in this sample with three ACEs, as evidenced by the large confidence interval.

Though no known research has explored the relationship between history of ACEs and removal decisions, these results were unanticipated. As discussed above, there is some evidence to suggest that when an individual has a personal history of abuse, they are more likely to believe a report of abuse (Cromer & Freyd, 2007, 2009; Jackson & Nuttall, 1994). The present study included only cases that had been supported for maltreatment; as such, it is assumed the caseworker believed the allegation of maltreatment. However, based on the findings that individuals with a personal history of childhood trauma are more likely believe an allegation of abuse, it would be unsurprising if they were also more likely to remove children from their homes. Nevertheless, this is not the relationship that was observed in this study.

It is possible that caseworkers with a history of more than one ACE were more tolerant of the risk of maltreatment. Perhaps caseworkers with more ACEs viewed the impact of abuse and neglect as not being too devastating because they themselves survived significant maltreatment. Or, if these caseworkers were influenced by heuristics, such as the availability heuristic discussed above, it is possible they weighted the outcome of their experiences heavily and felt their personal outcome was the most probable outcome for others, too. Conversely, from a utility perspective, these caseworkers may have experienced traumatic removals or separations from their parents and, as a result, placed more value on efforts to maintain family units.

In the Combined Sample, after also controlling for the Dalgleish scale and the Against Removal scale, ACEs were not a significant predictor of removal. This could be due to a variety of factors, including power. The Combined Sample only included caseworkers who completed each of the survey scales and, therefore, was the smallest sample. Nevertheless, because this study was exploratory and results were mixed, further research is needed to better understand the relationship between ACEs and removal decisions.

Proportion of Caseworkers with ACEs

The ACE survey used in this study enabled comparisons of the proportion of CPS caseworkers with ACEs to a U.S. and a Utah sample. The results are drastic. Compared to both the sample of the general population from 10 U.S. states and Washington D.C., the CPS caseworkers in this study had significantly more ACEs (Centers for Disease Control and Prevention, 2010). Just over 40% of individuals in the U.S. and Utah sample had no ACEs. This is in stark contrast to the pointedly lower 26% in the sample of CPS caseworkers. On the opposite end, between 14% and 16% of the U.S. and Utah samples had four or more ACEs. Conversely, approximately 27% of the CPS caseworkers had four or more ACEs. These findings are commensurate with other research that has found

ACEs are more prevalent among child service workers (Esaki & Larkin, 2013).

Though not the purpose of this study, it is important to note that a high prevalence of ACEs among caseworkers has implications for child welfare agencies. In recent years, there has been a national focus on creating child welfare agencies that are trauma informed. Trauma-informed agencies not only benefit the children and families involved, but also the child welfare caseworkers who are exposed to significant amounts of both direct and vicarious trauma on the job (Child Welfare Information Gateway, 2015). Research has found that individuals with personal trauma histories are more likely to develop secondary traumatic stress (Bride, Jones, & MacMaster, 2007). This places child welfare workers in precarious working conditions and, as will be discussed below, can also impact the children and families involved in child welfare services.

Predictive Ability Beyond Other Scales

The fourth research question was: Do any of the survey scales, two measuring self-reported attitudes and beliefs toward child safety and family preservation and one measuring childhood history of adverse events, have predictive ability beyond the others? This analysis included the three surveys and the control variables: the region in which the case was investigated, the number of previous investigations in which the child was involved, the age of the child, the race and ethnicity of the child, the gender of the caseworker, and the years of experience of the caseworker. In this model, none of the surveys were predictive of removal decisions after controlling for the case and organizational factors, as well as the caseworkers' gender and years of experience. This could be the result of relationships between predictors or differences between samples.

Or, as discussed above, this could be due to low power in the model as this was the smallest sample and this analysis included the most predictors. It is worth mentioning that, though not the variables of interest in this research question, caseworker years of experience both within and between caseworkers were significant predictors of removal in this model.

Implications

The results from this study provide support for the hypothesis in the DME that decision-maker factors influence the decisions they make. These findings suggested that caseworkers with more experience, male caseworkers, and caseworkers with more ACEs are less likely to remove children from their homes. Additionally, all caseworkers are more likely to remove children from their homes as they progress in their career with child welfare. Each of these characteristics represents sources of undesired variation in removal decisions. Accordingly, there is room for policy and practice interventions aimed at reducing inconsistencies in removal decisions.

Reducing Variance with Practice Changes

There are characteristics of the way problems are presented that can impact the options chosen. For example, framing effects have been shown to be influential in decisions (Covey, 2014; De Haan & Van Veldhuizen, 2015; Desser et al., 2013; Frisch, 1993; Gallagher & Updegraff, 2012; McNeil et al., 1982; Mishra et al., 2012; Sieck & Yates, 1997; Smith & Levin, 1996; Stanovich & West, 1998; Tversky & Kahneman, 1981). Kahneman and Tversky (1979) found that when a problem is framed as a loss, individuals are likely to make a riskier choice. Conversely, when problems are framed as gains, individuals are likely to make a safer choice. It is possible that consistently framing choices in child welfare removal decisions could lead to more consistent decisions. For example, if some caseworkers are framing decisions as a decision made to avoid future maltreatment then they may err on the side of child safety. On the other hand, if some caseworkers are framing the decision as a decision to avoid losing the family, they may err on the side of family preservation. Therefore, having consistent formal and informal language to frame and discuss decisions could assist in reducing unwanted variability in removal decisions.

Ideal circumstances for removal should be determined by individual child welfare agencies (Mansell, 2006) and, as such, the language through which cases will be discussed should be created to align with the goals and values of the agency. That is, if agencies are attempting to safely maintain children in their homes, it may be helpful to create language that highlights the strengths of the family and caregivers and to frame the decision in a way that highlights both the risk of new maltreatment and the trauma of being removed from the family. This language should be used in all aspects of CPS investigations, including formal means such as the risk and safety assessments, and informally, such as the way cases are staffed with supervisors.

Researchers have also found that framing effects can be reduced and choices more consistent when individuals are asked to provide rationales for their judgments and decisions (Almashat et al., 2008; S. Kim et al., 2005; P. M. Miller & Fagley, 1991; Sieck & Yates, 1997; Takemura, 1992). Providing rationales for decisions made during investigations could reduce variance in the choices. If, for example, caseworkers had to provide rationale for the items they endorse on safety and risk assessments, this could lead to more consistent assessments that contribute to the decision to remove children from their homes and reduce variation in interpretation in each of the criteria. Additionally, requiring rationale for each criterion would force caseworkers to think through the applicability of the criterion using more deliberate and analytic thought.

There is also evidence that having to explain a choice to others can reduce framing effects (Simon et al., 2004). As such, having a process for explaining or justifying removal decisions made may reduce variability. Though most decisions to remove children from their homes are presented and explained to others because most of the cases involving a removal are heard in front of a judge, when caseworkers opt to leave children in their homes and do not petition the court, it is possible that the caseworker may never have to explain the decision. Thus, a formal process where decisions to remove or not must be explained to others could potentially reduce variance in decision making. This could include a session with a supervisor where the decision and rationale for the decision is reviewed. This could also include a group or team review of the decision. In fact, it may be beneficial to present cases to a diverse team in terms of caseworkers with various years of experience, males and females, and caseworkers with childhood trauma so that perspectives of caseworkers who have differing removal tendencies are represented. Future research could investigate interventions such as these using methods with high internal validity, such as randomized control trials, to study their effectiveness.

As discussed above, the use of heuristics can influence decision making (Tversky

& Kahneman, 1974). Heuristics can provide helpful shortcuts in order to promote efficient decision making (Gigerenzer et al., 1999). However, in fields such as child welfare, where decisions are made under conditions of uncertainty, and individual feedback on long-term outcomes are not given, the development of expertise is not easily facilitated (Kahneman & Klein, 2009). Researchers have defined expert intuition as simply recognition of patterns (Chase & Simon, 1988).

Kahneman and Klein (2009) argued that to develop expert intuition there have to be valid clues that can be used to predict an event and that individuals must learn to detect those clues. Therefore, variability in decision making could be reduced if research better identified the best predictors of abuse and neglect. The field of risk prediction is advancing due to more data being collected in agency databases as well as advances in statistical techniques (Gillingham, 2016; Milner, Campbell, & Messing, 2017; White et al., 2015). Statistical methods of risk prediction are generally preferred to clinical assessments because clinical assessments can be "inconsistent, inequitable, biased, and inaccurate" (Milner et al., 2017, p. 36).

Despite these advances, many child welfare agencies continue to use risk assessment and structured decision-making tools that have low reliability and no criterion-validity studies (Bartelink et al., 2015). Child welfare systems could benefit from investing in risk prediction to identify the factors that best predict risk of maltreatment in their communities. Even the best risk assessment tools can be fallible if the individual collecting the data and conducting the assessment is not skilled at identifying those factors. Thus, CPS investigators must be better trained to recognize risk factors consistently.

Prior research has suggested that deliberate prolonged skills practice and feedback can facilitate the development of expertise (Camerer & Johnson, 1991; Ericsson, 2006; Ericsson et al., 2013; Kahneman & Klein, 2009). Skills practice should include learning sets of skills where skills become increasingly difficult. This deliberate practice should include immediate feedback from a highly skilled instructor. Therefore, it is likely that child welfare agencies would benefit from providing opportunities for caseworkers to practice skills such as investigation, completion of safety and risk tools, and in making removal decisions under the supervision of a coach who provides direct and explicit feedback on performance.

Feedback should also include quantitative feedback regarding the removal decisions caseworkers make (Kahneman & Klein, 2009). This could include feedback on outcomes, such as further instances of maltreatment and long-term outcomes for children and families, possibly provided through reports of safety, permanency, and well-being. Additionally, this could include a system for comparing removal decisions made between caseworkers. For example, if a caseworker decided to remove a child but children in situations similar to that child are typically not removed, the system could provide immediate feedback to the caseworker to consult with a supervisor or colleagues. This could help ensure consistent decisions are made.

Reducing Variance Through Personnel

Importantly, the purpose of this study was not to identify ideal removal decisions, nor was it to detect the characteristics of individuals who make fewer errors in their decisions. Rather, as indicated above, the study was designed to identify if there are characteristics of caseworkers that may lead to inconsistencies in removal decisions. Nevertheless, it is possible that one group is making better decisions than others. If future research finds that certain groups of caseworkers are making removal decisions consistent with the goals and values of child welfare agencies, then efforts focused on recruiting and retaining those individuals would be fruitful.

Currently, many child welfare jurisdictions across the U.S. are enhancing efforts to safely retain children in their homes (Administration for Children and Families, 2012). If, for example, future research determines caseworkers with multiple ACEs are making appropriate removal decisions that align with the goals and value of the agencies, recruiting and retaining individuals with a childhood history of trauma could help the agencies meet their goals of safely retaining children in their homes. At present, there are nationwide efforts to create trauma-informed systems (Administration for Children and Families, 2012). As discussed above, individuals with personal histories of trauma are at an increased risk for experiencing negative effects of the exposure to vicarious trauma, such as secondary traumatic stress. If the efforts to create trauma-informed systems are communicated to incoming social work students, it is possible those efforts could serve as a natural draw for individuals with a childhood history of trauma to the child welfare profession.

Caseworkers with a history of trauma are at a higher risk for secondary traumatic stress. Thus, they may be exiting the workforce due to symptoms of traumatic stress, compassion fatigue, or burnout. Retention of child welfare workers is a notoriously troublesome area for child welfare agencies and high turnover has come to be expected (Madden, Scannapieco, & Painter, 2014). A recent meta-analysis showed that organizational culture and climate was one of the largest predictors of employee retention (Kim & Kao, 2014). Thus, trauma-informed systems may reduce turnover of caseworkers who have histories of trauma if agencies are able to buffer the impact of vicarious trauma and support caseworkers who experience negative effects from the exposure to vicarious trauma.

Similarly, if male caseworkers are found to be making appropriate decisions that align with the goals and values of the child welfare agency, efforts to recruit and retain males may also help reduce unwanted variance in removal decisions and align removal decisions with the goals and values of child welfare agencies. Males are underrepresented in the field of child welfare. In this study, just over 30% of the survey respondents were male. That was slightly higher than national data which indicated males made up closer to 20% of child welfare workforces (Barth, Lloyd, Christ, Chapman, & Dickinson, 2008). Thus, exploring the traits of the males who perform well as CPS caseworkers and what drew these male caseworkers to child welfare would be helpful in recruiting and retaining males.

Limitations and Future Directions

This study employed an exploratory approach and many statistical tests were run. Thus, results may have limited generalizability or be significant by chance. Future research should use these study findings to inform study design and research questions in attempts to replicate these findings. Additionally, studies conducted in different child welfare settings are needed to assess whether these results are generalizable to agencies in different contexts and with dissimilar policy and practice guidelines.

A major limitation of this study is that, while the caseworkers' decisions over time were included, these data were modeled as cross-sectional data. This choice was made deliberately because survey data were not collected over time. However, this means any agency-wide trends in removals that occurred between 2008 and 2016 were not identified or controlled for in these models. If removals increased or decreased over time, this was not accounted for in these models and changes are confounded with the results. For example, it was noted above that the caseworkers who took the surveys had higher removal rates than the CPS Sample. While it could be that the sample of caseworkers who participated in the survey were more likely to remove, this may be a result of overall agency trends in removal rates when the survey was taken.

Similarly, attitudes and beliefs toward child safety and family preservation were applied to the caseworkers' histories of removal decisions. It is possible that these attitudes and beliefs change over time and so it is unsurprising that they do not significantly predict a caseworker's history of removal decisions. Additionally, without having a measure of attitude change over time, it was not possible to assess the impact of attitudes at various points in a caseworker's career. For example, attitudes could be more influential when a caseworker is new. Similarly, attitudes may be more influential during periods with different practice and policy standards.

Future research is needed to explore the impact of each of the variables longitudinally. Regarding these caseworker factors, research is needed to explore how attitudes change in relation to years of experience, organizational change including new policies and practices, and as a result of certain experiences, such as negative child outcomes. If, for example, attitudes towards child safety and family preservation are malleable, interventions could be designed to modify attitudes to match the goals and values of the child welfare agency. Additionally, researchers should investigate if these potential attitude changes correspond with removal decisions made over time.

This study also did not consider any interaction effects. Interactions were not planned in this exploratory study because of the numerous statistical tests that were run and anticipated problems with power. Future research should explore interactions between some of these main effects, such as an interaction between attitudes or gender and years of experience. Machine learning techniques may be helpful in elucidating whether interactions exist and subsequent research could examine any identified interactions from a more theoretical, confirmatory approach.

Not included in this study were the outcomes of the removal decisions, such as lower maltreatment rates of children, permanency outcomes, and overall well-being of the children and families. Thus, it cannot be concluded, for example, that caseworkers with more experience are making better decisions. Further research is needed to understand the relationship between the variables in this study and long-term outcomes. Additionally, research is needed to identify if there are characteristics of caseworkers that lead to better outcomes.

Though this study controlled for some case-level and organizational differences, there are likely other important variables that were not controlled for in this study. For example, the type of maltreatment has been shown to be a significant predictor of removals (Rossi et al., 1999; Stokes & Taylor, 2014). Additionally, a substantial amount of variance lies between families. Though predictors were included at the child-case level, no predictors were included to explain this variance between families. Similarly, though differences between regions were controlled for by including a fixed effect for region, no other organizational-level predictors were included in these models.

Another limitation of this study is that the child-case data used in this study were child welfare administrative data. Though administrative data can provide a wealth of information, the use of this type of data for research purposes is not without flaws (Drake & Jonson-Reid, 1999). Omissions and errors could have been made in data entry. Additionally, caseworkers may have varied in the way they recorded information, leading to systematic differences in data between caseworkers.

Finally, the ultimate purpose of this area of research is to identify actionable areas to reduce inconsistencies in the removal decisions made by CPS caseworkers. Accordingly, once sources of variability are identified with confidence, researchers should investigate if interventions, such as policy changes, practice changes, trainings, and support tools, can influence removal decisions to become more consistent and align with the goals and values of the child welfare agencies. Do, for example, efforts targeted at retaining caseworkers so that CPS workforces have greater experience lead to more consistent removal rates? As another example, does education around the influence of caseworker characteristics help reduce variability in removal decisions?

Conclusions

There is significant undesired variation in the removal decisions made by caseworkers. These inconsistencies are beyond variance explained by factors related to the case. These decisions deeply impact the lives of children and families that come into contact with child welfare agencies. This study used an exploratory approach to investigate if caseworker characteristics influence the removal decisions made by caseworkers. Further research is needed to replicate these findings and to explore the relationships between the variables in this study and removal decisions in different settings. Nevertheless, the results from this study suggested that caseworkers with more experience, male caseworkers, and caseworkers with more ACEs are less likely to remove children from their homes. Additionally, caseworkers become more likely to remove children from their homes as they progress in their career with DCFS. Each of these are potential areas that could be targeted by policy or practice interventions to reduce inconsistencies in removal decisions.

APPENDIX A

DCFS DIRECTOR EMAIL

Hello Region Staff,

DCFS is working with the University of Utah Social Research Institute (SRI) to get a better understanding of child welfare decision making. The goal of this study is to empirically identify what factors influence CPS removal decisions.

Your input is essential for us to get an accurate understanding of what influences the difficult decisions that must be made every day.

On Monday for the next three weeks, an e-mail with a link to a survey will be sent to each worker, supervisor, or regional administrator on a CPS case in the past twelve months. Each week's survey is different and should take you no more than 5-10 minutes to complete. The emails will come from utahsri@gmail.com.

Participation in this survey is voluntary; however, I hope you will take a few minutes to respond to each of the surveys. Your input will help provide us with important information needed to understand what is influencing decision making.

Thank you for the work you do every day. Utah's most vulnerable children and their families need your support.

Sincerely,

Brent Platt
DCFS Director

APPENDIX B

EMAIL SURVEY RECRUITMENT 1

You've been selected to participate in a CPS Decision-Making study as part of the DCFS IV-E waiver evaluation because you were identified as a worker on a CPS case in the past twelve months. The goal of this survey is to empirically identify what factors influence CPS removal decisions.

This is the first surveys you will receive over the next three weeks. Each survey should take about five minutes.

Please complete this brief survey now, or as soon as possible. Your views are crucial to having an accurate understanding of the factors that influence decision making in child welfare.

If you have any difficulty taking this survey or with this link, please contact Mindy Vanderloo at mindy.vanderloo@utah.edu.

APPENDIX C

EMAIL SURVEY RECRUITMENT 2

As you know, we have spent the past few weeks collecting surveys that will help us identify empirical factors that influence CPS decision making. The surveys are opened until the end of this week. Please take a moment now to complete the surveys. Your responses will help provide information on how CPS decisions are made, help us learn more about decision making, and help Utah continue to be a leader in child welfare!

Thank you!

APPENDIX D

AGAINST REMOVAL FROM HOME OF CHILDREN AT RISK SCALE

Indicate how much you agree with each of the following statements:

1. Even when parents emotionally abuse their child an effort should be made to keep him/her at home.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
2. Even when parents physically abuse their child an effort should be made to keep him/her at home.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
3. Even when parents neglect their child an effort should be made to keep him/her at home.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
4. If parents sexually abuse their child he/she should be removed from home.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
5. If a child is removed from home a serious effort should be made to reunify him/her with his parents as soon as possible.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
6. Even in a case where a child was removed from home because his parents neglected him/her, every effort should be made to reunify the child with his parents.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
7. Even in a case where a child was removed from home because he/she was emotionally abused by his/her parents, every effort should be made to reunify the child with his/her parents.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
8. Involving the child in the decision making process regarding his/her removal from home yields better decisions.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]
9. Most of the parents of children at risk are unable to make a good decision regarding the need for out of home placement for their child.	[1- Strongly agree | 2 | 3| 4- Neither agree nor disagree | 5 | 6 | 7- Strongly disagree]

APPENDIX E

DALGLEISH SURVEY

<u>Instructions</u>: In the following items you will be presented with a pair of statements. We want you to choose between them. We understand that you might endorse both statements but try to **choose the statement that best reflects *your* general work focus and beliefs**. Indicate your preference by circling A or B. You will see a statement more than once, but each pairing is different. There are no right or wrong answers. Please rate the strength of your preference on the following scale of one to five.

Very Weak 1	2	3	4	Very Strong 5

	Items	Which statement?	Strength of preference?
1.	Work should be focused on keeping the family together. Child protection workers should be willing to be an advocate for the child.	A B	1 2 3 4 5
2.	The client is the child and all other work is secondary. Work should be focused on keeping the family together.	A B	1 2 3 4 5
3.	Work should be focused on protecting the child. Work should be focused on keeping the family together.	A B	1 2 3 4 5
4.	Families are the best place for children to achieve their full potential. There is a need to ensure the physical and emotional well being of all children.	A B	1 2 3 4 5
5.	Children's rights should be safeguarded so they achieve their full potential. The family's right to guide the development of their children should be safeguarded.	A B	1 2 3 4 5
6.	Families are the best place for children to achieve their full potential. The state has a responsibility to protect children.	A B	1 2 3 4 5

7.	There is a need to ensure the physical and emotional well being of all children. The state should not be responsible for families or their children.	A B	1 2 3 4 5
8.	Families are the best place for children to achieve their full potential. Children's rights should be safeguarded so they achieve their full potential.	A B	1 2 3 4 5

APPENDIX F

ADVERSE CHILDHOOD EXPERIENCES SURVEY

Looking back, before you were 18,	
1. Did you live with anyone who was depressed, mentally ill, or suicidal?	Yes 1 | No 0 | Not Sure 2
2. Did you live with anyone who was a problem drinker or alcoholic?	Yes 1 | No 0 | Not Sure 2
3. Did you live with anyone who used illegal street drugs or who abused prescription medications?	Yes 1 | No 0 | Not Sure 2
4. Did you live with anyone who served time or was sentenced to serve time in a prison, jail, or other correctional facility?	Yes 1 | No 0 | Not Sure 2
5. Were your parents separated or divorced or was a parent lost to you through abandonment or other reason?	Yes 1 | No 0 | Not Sure 2
6. How often did your parents or adults in your home ever slap, hit, kick, punch or beat each other up?	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4
7. How often did a parent or adult in your home ever slap, kick, or physically hurt you?	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4
8. How often did a parent or adult in your home ever swear at you, insult you, or put you down?	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4
9. How often did anyone at least 5 years older than you or an adult, ever touch you sexually	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4
10. How often did anyone at least 5 years older than you or an adult, try to make you touch them sexually?	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4
11. And last one, how often did anyone at least 5 years older than you or an adult, force you to have sex?	Never 1 | Once 2 | More than Once 3 | Don’t know/Not Sure 4

12. I went to treatment for at least one of the negative experiences asked about above.	Yes 1 | No 0 | I did not experience any of the experiences asked about above 2
13. I found the treatment I received for the negative experience(s) helpful.	Very unhelpful 1 | 2| Neither helpful, nor unhelpful 3 | 4 | Very helpful 5 | I did go to treatment OR not experience any of these negative experiences 6

APPENDIX G

UNIVERSITY OF UTAH INSTITUTIONAL REVIEW BOARD APPROVAL

INSTITUTIONAL REVIEW BOARD
THE UNIVERSITY OF UTAH

75 South 2000 East Salt Lake City, UT 84112 | 801.581.3655 | IRB@utah.edu

IRB:	IRB_00064471
PI:	Matthew Davis
Title:	Title IVE Waiver
Date:	5/5/2016

This Amendment Application (DME and UFACET) qualifies for an expedited review by a designated University of Utah IRB member according to University IRB policy. The designated IRB member has reviewed and approved your amendment request for this study on 4/27/2016. The approval of the amendment is effective as of 5/5/2016. The approval of this amendment request does NOT change the expiration date of this research study as noted below.

Your study will expire on 9/18/2016 11:59 PM.
Any future changes to this study must be submitted to the IRB prior to initiation via an amendment form.

DETERMINATIONS

- **Waiver/Alteration Determination:** The IRB has determined that the request for **waiver of documentation of informed consent** as described in this application is approved for this research under 45 CFR 46.117(c).
- **Waiver/Alteration Determination:** The IRB has determined that the request for the **waiver of informed consent** as described in this application is approved for this research under 45 CFR 46.116(d).

APPROVED DOCUMENTS

Informed Consent Document
Survey Cover Letter Waiver IV-E 2016.DOC
Worker consent Waiver IV-E_4.2016_CLEAN.docx

Surveys, etc.
CPS Worker Observation Areas Waiver IV-E 2016.docx
4_2016 Decision Making substudy candidate survey questions.docx
SPANS instrument for UFACET-to-Service Plan Reviews

Click AM_00023789 to view the application and access the approved documents.

Please take a moment to complete our customer service survey. We appreciate your opinions and feedback.

APPENDIX H

UTAH DEPARTMENT OF HUMAN SERVICES INSTITUTIONAL REVIEW BOARD APPROVAL

State of Utah

GARY R. HERBERT
Governor

SPENCER J. COX
Lieutenant Governor

DEPARTMENT OF HUMAN SERVICES

ANN SILVERBERG WILLIAMSON
Executive Director

LANA STOHL
Deputy Director

MARK BRASHER
Deputy Director

Date: 4/6/2016

Primary Investigator: Matt Davis, PhD

DHS IRB Number: 0531
Please include this number on all subsequent correspondence

Subject: Title IVE Waiver Evaluation Project

DHS IRB Review finding: Final Approval

Thank you for your response to our previous letter and the modifications to your protocol. The Department of Human Services' Institutional Review Board (DHS IRB) has reviewed the modifications and approved the subject protocol.

Expiration date: 4/5/2017
You may not conduct any research after this expiration date unless you submit a continuing review resubmission form that is approved by the DHS IRB or one of its representatives. If you suspect that your research will continue beyond the expiration date you must complete the attached ongoing/amendment form along with a status report and resubmit for subsequent review and approval at least one month prior to expiration. If we have not received your resubmission prior to the expiration date, and if the research is ongoing, you will need to resubmit a full protocol application and request IRB approval. Additionally, data collected and/or analyzed during any period of time in which the IRB approval is not in effect, will have to be destroyed or discarded.

Approved documents:

Document Type	Document Name
Research Proposal	As per final proposal.
Informed Consent/Assent Documents	As per final proposal.
Recruitment	As per final proposal.
Surveys	As per final proposal.

Amendments:
In the event that any further changes are made to the research following this approval (e.g., changes in target population, materials to which subjects are to be exposed, procedures to be employed, etc.), please document these changes on the included amendment form and send it to the DHS IRB.

IRB Reviews:
During the course of research, the protocol is subject to review by the DHS IRB and/or the DHS Bureau of Internal Review and Audit (BIRA) to ensure consistency and compliance with the IRB approval. This may include observing the assent and consent process and reviewing other elements of the research as approved by the IRB.

DHS IRB contact information:
If you need further assistance, please contact Vanessa Amburgey, Division of Child and Family Services IRB Representative, at 801-538-4503 or vvallejo@utah.gov.

Final Report:
Once your research is completed, please send a copy of your final report to the DHS IRB to allow its members and the Department to benefit from your research findings.

Thank you for your cooperation during this review process and good luck in your endeavors.

Sincerely,

Frank M. Rees, Ph.D.

Bruce N Larsen

Frank M. Rees, Ph.D., Chair
Bruce N. Larsen, Co-Chair

DHS Institutional Review Board

c
Vanessa Amburgey

APPENDIX I

CONSENT COVER LETTER

Title IVE Wavier Evaluation Study Decision Making Sub-Study

The purpose of this research study is to understand the factors that influence removal decisions during CPS investigation. We are doing this study as part of the Title IV-E Waiver Demonstration evaluation

We are asking you to complete this survey on factors related to how decisions are made in child welfare. The survey asks questions about you or other professionals you work with regarding: about your background, perceptions of support for child welfare work, perceptions of leadership, your perceptions of community services, your thoughts on families, perception of skills, workload, and your personal history of adverse events. Your answers will assist us in determining the relative influence of these factors on removal decisions. There are no known risks or benefits to completing this survey.

Your survey responses will be matched to administrative data from the SAFE database. The researchers will not share your responses with anyone outside of the research team and identifying information will be destroyed by June 30, 2020. Results will be reported in aggregate form for groups of child welfare professionals, not individually. The investigators may use the results in reports, academic articles, conference presentations, and to meet the requirements for degree completion.

Contact the Institutional Review Board (IRB) if you have questions regarding your rights as a research participant. Also, contact the IRB if you have questions, complaints or concerns which you do not feel you can discuss with the investigator. The University of Utah IRB may be reached by phone at (801) 581-3655 or by e-mail at irb@hsc.utah.edu.

If you have any questions for the DCFS representative to the Department of Human Services IRB contact Vanessa Amburgey at vvallejo@utah.gov or at (801) 541-5705.If you have any questions complaints or if you feel you have been harmed by this research please contact Mindy Vanderloo, M.Ed., Social Research Institute, at (801)581-8841 or mindy.vanderloo@utah.edu.

This survey will be administered in four parts on different days. It should take about 10 minutes to complete each survey. Participation in this study is voluntary. You can choose not to take part. You can choose not to finish the questionnaire or omit any question you prefer not to answer without penalty or loss of benefits.

By completing the survey, you are giving your consent to participate.

Thank you for your time! We appreciate your input. Your views are crucial to having an accurate understanding of the factors that influence decision making in child welfare

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